Fuzzy TOPSIS based on α Level Set for Academic Staff Selection

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ABSTRACT

This paper applies the fuzzy TOPSIS based on α-level in solving a multi-criteria decision-making problem. The basic principle of fuzzy TOPSIS is that the chosen alternatives should have the shortest distance from the fuzzy positive ideal solution and the farthest distance from the fuzzy negative ideal solution in which can be determined by calculating the closeness coefficient. In this paper, the α-level set of the fuzzy closeness coefficient is calculated at eleven α levels. The closeness coefficient can be presented as a fuzzy number which generates a more accurate fuzzy estimation of the relative closeness. An empirical study of academic staff selection is conducted to illustrate its application.

Keywords: *academic staff selection, fuzzy TOPSIS, multi-criteria decision-making*

Introduction

Multi-criteria decision-making (MCDM) refers to screening, prioritising, ranking or selecting a set of alternatives under independent, incommensurate and conflicting criteria (Hwang & Yoon, 1981). A MCDM problem is characterised by the ratings of each alternative with respect to each criterion and the weights given to each criterion. Classical MCDM methods assume that the ratings of alternatives and the weights of criteria are crisp values. However, in the real world, information sources maybe unquantifiable, incomplete, unobtainable and partial ignorance (Chen & Hwang, 1992). Hence, the classical MCDM cannot handle problems in which the values of the ratings are linguistic terms represented by fuzzy sets. In order to cope with such a problem, fuzzy MCDM was developed and applied.

The general use of fuzzy set theory in MCDM is discussed in Chen and Hwang (1992), Ribeiro (1996) and Robert and Fuller (1996), while specific fuzzy MCDM methods can be found in Hsu and Chen (1997), Chen (2000), Cheng, Chan and Huang (2003) and Wang and Poh (2003). Ribeiro (1996) proposed fuzzy decision making with partial preference while Hsu and Chen (1997) applied fuzzy credibility relation (FCR) method in ranking alternatives under multiple criteria. In another study, Chen (2000) extended the concept of technique for order performance by similarity to ideal solution (TOPSIS) for solving MCDM problems in fuzzy environment. The classical TOPSIS method was first proposed by Hwang and Yoon (1981) based on the concept that the chosen alternative should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. Inspired by Chen's approach, Wang and Elhag (2006) proposed a fuzzy TOPSIS based on α level set in bridge risk assessment. Findings by Wang and Elhag (2006) led to a fuzzy relative closeness for each alternative compared to a crisp relative closeness for each alternative using TOPSIS method as in Chen (2000). Crisp relative closeness provides only one possible solution to a fuzzy MCDM problem in which cannot reflect the whole picture of its all solution and, therefore, the advantage of collecting fuzzy data becomes unapparent.

This paper applied the fuzzy TOPSIS based on α level set as in Wang and Elhag (2006) in selecting the academic staff at the Department of Mathematics and Statistics Universiti Teknologi MARA (UiTM) Pahang. This study shows an alternative way of selecting academic staff in UiTM Pahang by using analytical method compared to individual perception and human intuition in the traditional process of selection. The result can help the management in choosing the best candidate based on the vague and imprecise performance ratings by the decision maker.

Preliminaries

Definition 1

A triangular fuzzy number $\tilde{N}$ can be defined by a triplet (n_1, n_2, n_3). The membership function $\mu_{\tilde{N}}(x)$ is defined as follows.

$$\mu_{\tilde{N}}(x)=\begin{cases}\dfrac{x-n_1}{n_2-n_1} & ,n_1\le x\le n_2\\ \dfrac{x-n_3}{n_2-n_3} & ,n_2\le x\le n_3\\ 0 & ,otherwise\end{cases}$$

Definition 2

The α-level sets or α-cuts of fuzzy number $\tilde{P}$ is defined as $P_\alpha=\{x\in X,\mu_{\tilde{P}}(x)\ge\alpha\}$ and $\alpha\in[0,1]$.

Fuzzy Topsis

TOPSIS, one of the known classical MCDM methods, was first developed by Hwang and Yoon (1981) for solving a MCDM principle. The basic principle of TOPSIS is that the chosen alternatives should have the shortest distance from the positive ideal solution and the farthest distance from the negative ideal solution. The performance ratings and the weights of the criteria in TOPSIS method are given as crisp values. Since human judgement is often vague and unable to estimate with an exact numerical value, crisp data are inadequate to model real life situations. Hence, Chen (2000) extended the concept of TOPSIS and proposed a methodology for solving MCDM in fuzzy environment.

The procedure of TOPSIS method as in Chen (2000) is as follows:

1. Build a fuzzy decision criteria matrix $\tilde{X}=(\tilde{x}_{ij})_{m\times n}$ where $\tilde{x}_{ij}$ is a linguistic variable and can be described by triangular fuzzy number, $\tilde{x}_{ij}=(a_{ij},b_{ij},c_{ij})$.

2. Normalise the fuzzy decision matrix $\tilde{X}=(\tilde{x}_{ij})_{m\times n}$ as $\tilde{R}=(\tilde{r}_{ij})_{m\times n}$ where $\tilde{r}_{ij}=\left(\dfrac{a_{ij}}{c^*_j},\dfrac{b_{ij}}{c^*_j},\dfrac{c_{ij}}{c^*_j}\right)$ and $c^*_j=\max_i c_{ij}$.

3. Construct the weighted normalised decision matrix as $\tilde{V}=[\tilde{v}_{ij}]_{m\times n}$, $i=1,2,\ldots,m$, $j=1,2,\ldots,n$ where $\tilde{v}_{ij}=\tilde{r}_{ij}(\cdot)\tilde{w}_j$, $\tilde{w}_j$ is the relative weight of the j-th criteria and $\sum_{j=1}^{n}w_j=1$.

4. Determine the positive (A^*) and negative (A^-) ideal solutions as
$$A^* = \left(\tilde{v}^*{}_1, \tilde{v}^*{}_2, \ldots, \tilde{v}^*{}_n\right)$$
$$A^- = \left(\tilde{v}^-{}_1, \tilde{v}^-{}_2, \ldots, \tilde{v}^-{}_n\right)$$
where $\tilde{v}^*{}_j = (1,1,1)$ and $\tilde{v}^-{}_j = (0,0,0)$.

5. Calculate the separation measure by using the n-dimensional Euclidean distance as defined in Chen (2000).
The separation of each alternative from A^* and A^- is given as:
$\tilde{d}^*{}_i = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}^*{}_j\right)$ and $\tilde{d}^-{}_i = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}^-{}_j\right)$ where
$d(\tilde{m},\tilde{n}) = \sqrt{\frac{1}{3}\left[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2\right]}$, $\tilde{m} = (m_1, m_2, m_3)$
and $\tilde{n} = (n_1, n_2, n_3)$ are triangular numbers.

6. Calculate the relative closeness of each alternative to the ideal solution. The relative closeness of the alternative A_i with respect to A^* is defined as:
$$RC_i = \frac{\tilde{d}^-{}_i}{\tilde{d}^*_i + \tilde{d}^-{}_i}$$

7. Rank the alternatives according to the relative closeness to the ideal solution. The bigger the RC_i, the better the alternative A_i. The best alternative is the one with the greatest relative closeness to the ideal solution.

Fuzzy Topsis Based on α Level Set

Chen (2000) defines the Euclidean distance of two triangular fuzzy numbers $\tilde{m} = (m_1, m_2, m_3)$ and $\tilde{n} = (n_1, n_2, n_3)$ as

$d(\tilde{m},\tilde{n}) = \sqrt{\frac{1}{3}\left[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2\right]}$. This Euclidean distance is a crisp value. Based on the TOPSIS procedure discussed before, the Euclidean distance of each alternative to the positive and negative ideal solution is both crisp which leads to a crisp point estimate for the relative closeness of each alternative. Since the fuzzy MCDM problem is defuzzified into a crisp value at the early stage, then the advantage of collecting fuzzy data becomes unapparent.

To overcome the shortcomings, Wang and Elhag (2006) proposed a fuzzy TOPSIS based on α level set. The fuzzy TOPSIS based on α level set is presented as below.

Let $\widetilde{X} = (\widetilde{x}_{ij})_{m \times n}$ be a fuzzy decision matrix and $\widetilde{W} = (\widetilde{w}_1, \widetilde{w}_2, \mathrm{K}, \widetilde{w}_n)$ be fuzzy weights. $\widetilde{x}_{ij} = (a_{ij}, b_{ij}, c_{ij})$ and $\widetilde{w}_j = (w_{j1}, w_{j2}, w_{j3})$ for i = 1,2,…,m and j = 1,2,…,n are triangular fuzzy numbers. The normalised decision matrix can be written as

$\widetilde{R} = [\widetilde{r}_{ij}]_{m \times n}$ where

$$\widetilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*} \right) \text{ and } c_j^* = \max_i c_{ij} \text{ for } j \in B;$$

$$\widetilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{c_{ij}} \right) \text{ and } a_j^- = \min_i a_{ij} \text{ for } j \in C;$$

B and C are the set of benefit criteria and cost criteria respectively.

Normalised $\widetilde{r}_{ij}$ are still triangular fuzzy numbers. Let $(r_{ij})_\alpha = [(r_{ij})_\alpha^L, (r_{ij})_\alpha^U]$ and $(w_j)_\alpha = [(w_j)_\alpha^L, (w_j)_\alpha^U]$ be the α level sets of $\widetilde{r}_{ij}$ and $\widetilde{w}_j$.

Based on the definition of relative closeness in Chen (2000), the relative closeness of the alternative i can be equivalently written as

$$RC_i = \frac{\sqrt{\sum_{j=1}^{n} (w_j r_{ij})^2}}{\sqrt{\sum_{j=1}^{n} (w_j r_{ij})^2} + \sqrt{\sum_{j=1}^{n} (w_j (r_{ij} - 1))^2}}, \text{ for } i = 1,2,\mathrm{K},m,$$

$$(w_j)_\alpha^L \le w_j \le (w_j)_\alpha^U \text{ and } (r_{ij})_\alpha^L \le r_{ij} \le (r_{ij})_\alpha^U \text{ for } j = 1,2,\mathrm{K},n.$$

RC_i is an interval whose lower and upper bounds can be captured using the following pair of fractional programming models:

$$(RC_i)_\alpha^L = \min \frac{\sqrt{\sum_{j=1}^{n}(w_j r_{ij})^2}}{\sqrt{\sum_{j=1}^{n}(w_j r_{ij})^2} + \sqrt{\sum_{j=1}^{n}(w_j(r_{ij}-1))^2}}$$

s.t. $(w_j)_\alpha^L \le w_j \le (w_j)_\alpha^U, (r_{ij})_\alpha^L \le r_{ij} \le (r_{ij})_\alpha^U$ for j = 1, 2, K, n.

$$(RC_i)_\alpha^U = \max \frac{\sqrt{\sum_{j=1}^{n}(w_j r_{ij})^2}}{\sqrt{\sum_{j=1}^{n}(w_j r_{ij})^2} + \sqrt{\sum_{j=1}^{n}(w_j(r_{ij}-1))^2}}$$

s.t $(w_j)_\alpha^L \le w_j \le (w_j)_\alpha^U, (r_{ij})_\alpha^L \le r_{ij} \le (r_{ij})_\alpha^U$ for j = 1, 2, K, n.

RC_i is monotonically increasing functions of r_{ij} ($j = 1,2,\text{K}\ ,n$), which means RC_i reaches its maximum and minimum at $r_{ij} = (r_{ij})_\alpha^U$ and $r_{ij} = (r_{ij})_\alpha^L$ respectively. Therefore, the pair of fractional programming models can be simplified as

$$(RC_i)_\alpha^L = \min \frac{\sqrt{\sum_{j=1}^{n}\left(w_j (r_{ij})_\alpha^L\right)^2}}{\sqrt{\sum_{j=1}^{n}\left(w_j (r_{ij})_\alpha^L\right)^2} + \sqrt{\sum_{j=1}^{n}\left(w_j (r_{ij})_\alpha^L - 1\right)^2}}$$

s.t $(w_j)_\alpha^L \le w_j \le (w_j)_\alpha^U$ for j = 1, 2, K, n.

$$(RC_i)_\alpha^U = \min \frac{\sqrt{\sum_{j=1}^{n}\left(w_j (r_{ij})_\alpha^U\right)^2}}{\sqrt{\sum_{j=1}^{n}\left(w_j (r_{ij})_\alpha^U\right)^2} + \sqrt{\sum_{j=1}^{n}\left(w_j (r_{ij})_\alpha^U - 1\right)^2}}$$

s.t $(w_j)_\alpha^L \le w_j \le (w_j)_\alpha^U$ for j = 1, 2, K, n.

In order to select the best alternative, the fuzzy relative closeness RC_i has to be defuzzified. The simplest defuzzification method based on α level set is built by applying the averaging level cut (ALC) (Oussalah, 2002). By using ALC, the defuzzified value of RC_i for N α level sets can be calculated by $\left(RC_i\right)^*_{ALC} = \frac{1}{N}\sum_{j=1}^{N}\left[\frac{\left(RC_i\right)^L_{\alpha_j} + \left(RC_i\right)^U_{\alpha_j}}{2}\right]$.

Academic Staff Selection in UiTM Pahang: An Empirical Study

The traditional process of the academic staff selection in UiTM Pahang is based on the interviewers' or decision makers' individual perception on the candidates. Although, a guideline consisting of four criteria (voice tone, appearance, presentation and audio visual) has been prepared by the management, there has been no analysis ever done on it. The selection has almost been based on human intuition which is vague, uncertain and immeasurable. No proper measurement has been done to support the decision. Therefore, this study is conducted as an alternative way of selecting academic staff in UiTM Pahang by using an analytical method.

The present study attempted to apply the fuzzy TOPSIS based on α level set method on the selection of an academic staff in the Department of Mathematics and Statistics UiTM Pahang. The method was applied on the recent selection exercise. This process is demonstrated below.

The Department of Mathematics and Statistics UiTM Pahang wanted to select an academic staff among three candidates, A_1, A_2 and A_3. A committee of three decision makers, D_1, D_2 and D_3 evaluated the candidates against five benefit criteria which are academic qualification (C_1), oral communication skills (C_2), English proficiency (C_3), self-confidence (C_4) and teaching skills (C_5). The hierarchical structure of this decision-making problems is shown in Figure 1. The relative importance weights of the five criteria are described using linguistic variables with hedges such as very low, low, medium low, medium, medium high, high and very high as shown in Table 1. The ratings are also characterised by linguistic variable with hedges such as very poor, poor, medium poor, fair, medium good, good and very good (Table 2).

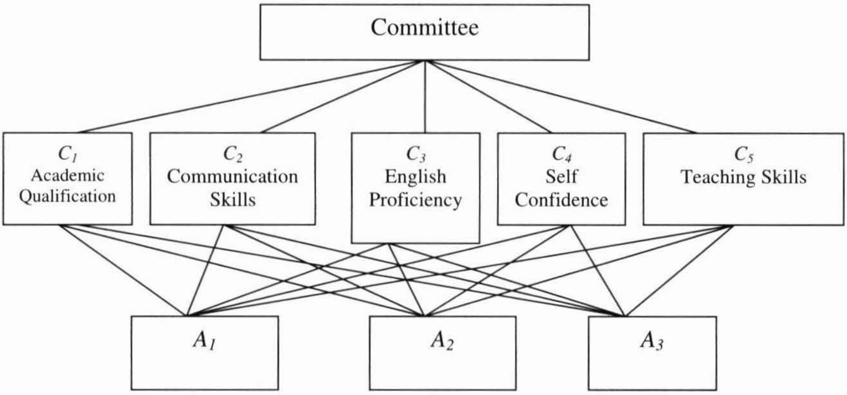

Figure 1: The Hierarchical Structure

Table 1: Linguistic Variables for the Relative Importance Weights of Five Criteria

Linguistic Variable	Fuzzy Number
Very low (*VL*)	(0, 0, 0.1)
Low (*L*)	(0, 0.1, 0.3)
Medium low (*ML*)	(0.1, 0.3, 0.5)
Medium (*M*)	(0.3, 0.5, 0.7)
Medium high (*MH*)	(0.5, 0.7, 0.9)
High (*H*)	(0.7, 0.9, 1.0)
Very high (*VH*)	(0.9, 1.0, 1.0)

Table 2: Linguistic Variables for the Ratings

Linguistic Variable	Fuzzy Number
Very poor (*VP*)	(0, 0, 1)
Poor (*P*)	(0, 1, 3)
Medium poor (*MP*)	(1, 3, 5)
Fair (*F*)	(3, 5, 7)
Medium good (*MG*)	(5, 7, 9)
Good (*G*)	(7, 9, 10)
Very good (*G*)	(9, 10, 10)

Results

The three decision makers expressed their opinion on the importance of weights of five criteria and the ratings of each candidate with respect to the five criteria independently. Tables 3 and 4 show the assessment provided by the three decision makers and the aggregated fuzzy number. The calculation of the aggregated fuzzy number is based on Chen (2000, p. 5) which states that for *K* decision makers, the aggregated fuzzy number of each criterion and the relative weight of each criterion are defined as $\tilde{x}_{ij} = \frac{1}{K}\left[\tilde{x}_{ij}^{1}(+)\tilde{x}_{ij}^{2}(+)\mathrm{K}\ (+)\tilde{x}_{ij}^{K}\right]$ and $\tilde{w}_{j} = \frac{1}{K}\left[\tilde{w}_{j}^{1}(+)\tilde{w}_{j}^{2}(+)\mathrm{K}\ (+)\tilde{w}_{j}^{K}\right]$.

Table 3: The Relative Importance of Weights of the Criteria by Decision Maker

	D_1	D_2	D_3	Aggregated fuzzy number
C_1	*VH*	*VH*	*VH*	(0.9, 1.0, 1.0)
C_2	*VH*	*H*	*H*	(0.77, 0.93, 1.0)
C_3	*H*	*H*	*H*	(0.7, 0.9, 1.0)
C_4	*H*	*VH*	*MH*	(0.7, 0.87, 0.97)
C_5	*MH*	*VH*	*H*	(0.7, 0.87, 0.97)

Table 4: Ratings of Candidates with Respect to the Criteria by the Decision Maker

Criteria	Candidates	Decision maker			Aggregated fuzzy number
		D_1	D_2	D_3	
C_1	A_1	*MG*	*MG*	*G*	(5.7, 7.7, 9.3)
	A_2	*G*	*MG*	*G*	(6.3, 8.3, 9.7)
	A_3	*G*	*G*	*G*	(7, 9, 10)
C_2	A_1	*MG*	*F*	*F*	(3.7, 5.7, 7.7)
	A_2	*G*	*G*	*G*	(7, 9, 10)
	A_3	*G*	*MG*	*MG*	(5.7, 7.7, 9.3)
C_3	A_1	*F*	*F*	*MG*	(3.7, 5.7, 7.7)
	A_2	*G*	*G*	*VG*	(7.6, 9.3, 10)
	A_3	*G*	*MG*	*MG*	(5.7, 7.7, 9.3)
C_4	A_1	*F*	*F*	*G*	(4.3, 6.3, 8)
	A_2	*G*	*MG*	*G*	(6.3, 8.3, 9.7)
	A_3	*G*	*MG*	*G*	(6.3, 8.3, 9.7)
C_5	A_1	*F*	*F*	*G*	(3.7, 5.7, 7.7)
	A_2	*G*	*MG*	*G*	(7, 9, 10)
	A_3	*G*	*MG*	*G*	(6.3, 8.3, 9.7)

Table 5 shows the normalised fuzzy decision matrix and fuzzy weights.

Table 5: The Normalised Fuzzy Decision Matrix and Fuzzy Weights

	C_1	C_2	C_3	C_4	C_5
A_1	(0.57, 0.77, 0.93)	(0.37, 0.57, 0.77)	(0.37, 0.57, 0.77)	(0.44, 0.65, 0.82)	(0.37, 0.57, 0.77)
A_2	(0.63, 0.83, 0.97)	(0.7, 0.9, 1.0)	(0.76, 0.93, 1.0)	(0.65, 0.86, 1.0)	(0.7, 0.9, 1.0)
A_3	(0.7, 0.9, 1.0)	(0.57, 0.77, 0.93)	(0.57, 0.77, 0.93)	(0.65, 0.86, 1.0)	(0.63, 0.83, 0.97)
Weight	(0.9, 1.0, 1.0)	(0.77, 0.93, 1.0)	(0.7, 0.9, 1.0)	(0.7, 0.87, 0.97)	(0.7, 0.87, 0.97)

The fuzzy relative closeness at different α-level is shown in Table 6.

Table 6: α-level Set of the Fuzzy Relative Closeness of the Three Candidates

	Candidates		
α	A_1	A_2	A_3
0	[0.426, 0.814]	[0.68, 0.987]	[0.622, 0.956]
0.1	[0.447, 0.795]	[0.7, 0.978]	[0.642, 0.944]
0.2	[0.467, 0.777]	[0.72, 0.968]	[0.663, 0.931]
0.3	[0.487, 0.759]	[0.74, 0.957]	[0.683, 0.918]
0.4	[0.507, 0.740]	[0.76, 0.946]	[0.703, 0.905]
0.5	[0.527, 0.722]	[0.78, 0.934]	[0.723, 0.891]
0.6	[0.548, 0.703]	[0.799, 0.923]	[0.743, 0.878]
0.7	[0.568, 0.684]	[0.819, 0.912]	[0.763, 0.864]
0.8	[0.588, 0.666]	[0.838, 0.9]	[0.783, 0.85]
0.9	[0.608, 0.647]	[0.858, 0.889]	[0.802, 0.836]
1	[0.628, 0.628]	[0.877, 0.877]	[0.822, 0.822]

Therefore, the fuzzy relative closeness for candidates A_1, A_2 and A_3 are RC_1 = [0.426, 0.628, 0.814], RC_2 = [0.68, 0.877, 0.987] and RC_3 = [0.622, 0.822, 0.956] respectively and it is shown in Figure 2. The defuzzified values and the ranking of each candidate are shown in Table 7.

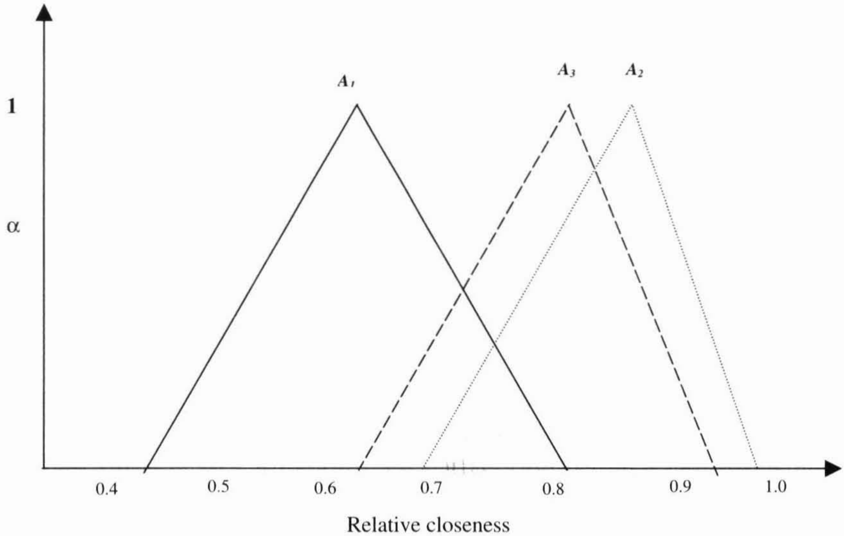

Figure 2: The Fuzzy Relative Closeness

Table 7: Defuzzified Value and Ranking of the Three Candidates

Candidates	Defuzzified value	Rank
A_1	0.624	3
A_2	0.856	1
A_3	0.807	2

Table 8: Comparisons of Results

Candidates	Chen's approach	Fuzzy TOPSIS based on α-level
	Relative closeness	Defuzzified value
A_1	0.55	0.624
A_2	0.72	0.856
A_3	0.69	0.807

Discussion

In this study, the fuzzy TOPSIS based on α-level set is applied in solving problem of academic staff selection. The relative closeness of each alternative is presented as a fuzzy number and is calculated at 11 α-level using Mathcad software. The fuzzy relative closeness is accurate enough by using the 11 α-level which are at $\alpha = 0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9$, and 1. The more α-level values used, the more accurate fuzzy relative closeness will be. The defuzzified values computed using ALC as in Ousallah (2002) are $RC_{A1} = 0.624$, $RC_{A2} = 0.856$ and $RC_{A3} = 0.807$, which give the ranking of $A_2 > A_3 > A_1$ as in Table 7. Table 8 shows a comparison of results using fuzzy TOPSIS by Chen (2000) and the fuzzy TOPSIS based on α-level set. Chen's approach obtained the relative closeness as 0.55 for A_1, 0.72 for A_2 and 0.69 for A_3 which are significantly lower than the defuzzified values. Although Chen's approach leads to the same ranking, it produces only a crisp value for the relative closeness while the fuzzy TOPSIS based on α-level set generates a more accurate fuzzy estimation of the relative closeness. The fuzzy TOPSIS based on α-level set method also defuzzified the imprecise values at the end of the process and not at the very beginning of the process which is the rationale of using fuzzy method. The fuzzy TOPSIS based on α-level set method also generates a more accurate fuzzy estimation of the relative closeness compared to Chen's approach.

Conclusion

Since multi-criteria decision problems generally involve uncertainty, fuzzy MCDM has been widely applied in solving real world decision-making problem. This paper has presented a fuzzy TOPSIS based on α-level in solving problem of an academic staff selection in the Department of Mathematics and Statistics UiTM Pahang. Based on the vague and imprecise performance ratings by the decision makers, the management can select the best candidate with five evaluated criteria which are academic qualification, communication skills, English proficiency, self confidence and teaching skills. This method is based on the holistic criteria of all the candidates and not only by looking at one or two criteria that may impress the decision makers. It combines all the criteria of the candidates with the decision makers' description. Up till now, there has been no exact mechanism in staff selection that looks into all the criteria as suggested by this method. Therefore, this analytical method is hoped to be an alternative way of selecting academic staff in UiTM Pahang compared to individual perception and human intuition in the traditional process. For future studies, it is suggested that a system can be developed in selecting staff in UiTM based on the TOPSIS algorithm. The coming system can be applied not only for selection of academic staff but also to the non-academic staff.

References

Chen, C.T. (2000). Extension of the TOPSIS for group decision making under fuzzy environment. *Fuzzy Sets and Systems*, *114*, 1-9.

Chen, S.J. & Hwang, C.L. (1992). *Fuzzy multiple attribute decision making: Methods and applications*. Berlin: Springer-Verlag.

Cheng, S., Chan, C.W. & Huang, G.H. (2003). An integrated multi criteria decision analysis and inexact mixed integer linear programming approach for solid waste management. *Engineering Applications of Artificial Intelligence*, *16*, 543-554.

Hsu, H.M. & Chen, C.T. (1997). Fuzzy credibility relation method for multiple criteria decision making problems. *Intelligent System, 96*, 79-91.

Hwang, C.L. & Yoon, K.P. (1981). *Multiple attribute decision making: Methods and applications*. Berlin: Springer.

Oussalah, M. (2002). On the compatibility between defuzzification and fuzzy arithmetic operations. *Fuzzy Sets and Systems*, *128*, 247-260.

Ribeiro, R.A. (1996). Fuzzy multiple attribute decision making: A review and new preference elicitation technique. *Fuzzy Sets and Systems*, *78*, 155-181.

Robert, C.C. & Fuller, R. (1996). Fuzzy multiple criteria making: Recent developments. *Fuzzy Sets and Systems*, *78*, 139-153.

Wang, W. & Poh, K.L. (2003, October 9-11). *Fuzzy MCDM based on confidence analysis*. Paper presented at the Tenth International Association for Fuzzy Set Management and Economy Congress, Leon, Spain.

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.

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