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A Dynamic Fuzzy Group Decision Making Method for Supplier Selection

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Abstract: We present a novel Dynamic Fuzzy Sets (DFS) method, which is the generalization of Fuzzy Sets (FS) and the dynamization of Interval-Valued Intuitionistic Fuzzy Sets (IVIFS). First, we propose some weighted DFS models from IVIFS. Second, we introduce the corresponding ranking function of DFS. Finally, we apply the DFS models and their ranking functions to supplier selection to demonstrate the advantages of these DFS models and the experimental results show that these DFS models are more effective than some IVIFS models in supplier selection.

Key words: IVIFS, DFS, multiple attribute decision making

INTRODUCTION

Zadeh (1965) launched fuzzy sets (FS). Atanassov (1986) proposed Intuitionistic Fuzzy Sets (IFS) and (Zhang *et al.*, 2013) interval-valued intuitionistic fuzzy sets (IVIFS), which generalized the FS theory. Hence, many researchers studied IFS and IVIFS and applied them to decision making widely (Chen and Tan, 1994; Hong and Choi, 2000; Kavita *et al.*, 2009; Xu, 2010; Li, 2010; Wang *et al.*, 2011; Feng *et al.*, 2012). However, most of the classic methods are suitable for static model and unsuitable for dynamic model. Taking this into account, Xu and Yager (2008) presented a dynamic decision making model, which was also studied by Wei (2009) and Su *et al.* (2011). However, traditional decision analysis models on IFS and IVIFS do not involve the detachment of the absent party. In order to overcome this disadvantage, we present some dynamic intuitionistic fuzzy sets method derived from intuitionistic fuzzy sets (Zhang *et al.*, 2012a, b, c). In this study, from IVIFS, we present a novel Dynamic Fuzzy Sets (DFS) method and some DFS models, which are the dynamization of IVIFS.

First, we present the concept of DFS and introduce the construction method of DFS. And then, we propose some DFS models and their ranking functions. Finally, we apply these DFS models along with their ranking functions to supplier selection. By comparing with the results from traditional IVIFS TOPSIS method, we conclude that these DFS models are more comprehensive and flexible than the IVIFS model. Thus, the model of DFS is valuable for the application of FS to multiple attribute group decision making and it is also useful for the dynamization of fuzzy reasoning, fuzzy decision making, interval-valued intuitionistic fuzzy reasoning and interval-valued intuitionistic fuzzy decision making.

CONSTRUCTION OF DFS

Definition 1: An IVIFS A in universe X is given by Atanassov and Gargov (1989):

$$\begin{cases} A = \{<M_A(x), N_A(x)>| x \in X\} \\ M_A(x) = [u_A^-(x), u_A^+(x)] \subseteq [0,1] \\ N_A(x) = [v_A^-(x), v_A^+(x)] \subseteq [0,1] \\ u_A^+(x) + v_A^+(x) \le 1 \end{cases} \quad (1)$$

Where $M_A(x)$ and $N_A(x)$ denote the interval of membership degree and the interval of non-membership degree of x to A, respectively.

Let:

$$\pi_A^-(x) = 1 - u_A^+(x) - v_A^+(x) \in [0,1]$$
$$\pi_A^+(x) = 1 - u_A^-(x) - v_A^-(x) \in [0,1]$$
$$H_A(x) = [\pi_A^-(x), \pi_A^+(x)]$$

For $\lambda_1(x) \in [0,1]$ we get DFS definition as follows.

Definition 2: A DFS A_1* derived from IVIFS in universe X is denoted by:

$$\begin{cases} A_1^* = \{<x, \mu_{A1}^*(x), v_{A1}^*(x)>| x \in X\} \\ \mu_{A1}^*(x) = \mu_A^-(x) + \lambda_1(x)\pi_A^+(x) \\ v_{A1}^*(x) = v_A^-(x) + (1-\lambda_1(x))\pi_A^+(x) \end{cases} \quad (2)$$

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$\mu^*_{A1}(x)$ and $\nu^*_{A1}(x)$ are membership function and non-membership function of x to A, respectively.

From definition 2, let all sample data be divided into three parts, $\mu^-_A(x)$ being the firm support party of event A, $\nu^-_A(x)$ representing the firm opposition party of event A and $\pi^+_A(x)$ showing all the absent party that may become either the support party or the opposition party. In the absent party, if there is $\lambda(x)\pi^+_A(x)$ sample supporting event A and $(1-\lambda(x))\pi^+_A(x)$ sample opposing event A, we have DFS denoted by definition 2. Obviously, DFS is an extension of FS and a dynamic method of IVIFS.

Similarly, for $\lambda_2(x)\epsilon[0, 1]$ we can define DFS as follows.

Definition 3: A DFS A_2* derived from IVIFS in universe X is denoted by:

$$\begin{cases} A^*_2 = \{< x, \mu^*_{A2}(x), \nu^*_{A2}(x) > | x \in X\} \\ \mu^*_{A2}(x) = \mu^+_A(x) + \lambda_2(x)\pi^-_A(x) \\ \nu^*_{A2}(x) = \nu^+_A(x) + (1-\lambda_2(x))\pi^-_A(x) \end{cases} \tag{3}$$

$\mu^*_{A2}(x)$ and $\nu^*_{A2}(x)$ are membership function and non-membership function of *x* to A, respectively.

Theorem 1: Let A be a DFS, then:

$$\mu^*_{A1}(x) + \nu^*_{A1}(x) = \mu^*_{A2}(x) + \nu^*_{A2}(x) = 1$$

According to definition 2 and definition 3, we have theorem 1.

From definition 2 and definition 3, we have definition 4 as follows.

Definition 4: A DFS A* derived from IVIFS in universe X can be also denoted by:

$$\begin{cases} A^* = \{< x, \mu^*_A(x), \nu^*_A(x) > | x \in X\} \\ \mu^*_A(x) = \lambda(x)(\mu^-_A(x) + \lambda_1(x)\pi^+_A(x)) \\ +(1-\lambda(x))(\mu^+_A(x) + \lambda_2(x)\pi^-_A(x)) \\ \nu^*_A(x) = \lambda(x)[\nu^-_A(x) + (1-\lambda_1(x))\pi^+_A(x)] \\ +(1-\lambda(x))[\nu^+_A(x) + (1-\lambda_2(x))\pi^-_A(x)] \\ \lambda(x) \in [0,1], \lambda_1(x) \in [0,1], \lambda_2(x) \in [0,1] \end{cases} \tag{4}$$

Where $\lambda(x)$ and 1-$\lambda(x)$ denote the weight of $\mu^*_{A1}(x)$ and the weight of $\mu^*_{A2}(x)$ and $\mu^*_A(x)$ and $\nu^*_A(x)$ are membership function and non-membership function of x to A, respectively.

According to the membership function of DFS from definition 4, a weighted ranking function can be defined as follows:

$$\begin{aligned} R_{DFS}(A^*) &= \sum_{x\in X} w_A(x)\mu^*_A(x) \\ &= \sum_{x\in X} w_A(x)[\lambda(x)\mu^*_{A1}(x) + (1-\lambda(x))\mu^*_{A2}(x)] \end{aligned} \tag{5}$$

Where $w_A(x)$ denotes the weight of element *x* and we have

$$w_A(x), \sum_{x\in X} w_A(x) = 1$$

According to definition 4, we have:

$$\begin{aligned} R_{DFS}(A^*) = \sum_{x\in X} w_A(x)[\lambda(x)(\mu^-_A(x) + \lambda_1(x)\pi^+_A(x)) \\ +(1-\lambda(x))(\mu^+_A(x) + \lambda_2(x)\pi^-_A(x))] \end{aligned} \tag{6}$$

If $\lambda(x) = 1$, we obtain:

$$R_{DFS}(A^*) = \sum_{x\in X} w_A(x)(\mu^-_A(x) + \lambda_1(x)\pi^+_A(x)) \tag{7}$$

If $\lambda(x) = 0.5$, we obtain:

$$\begin{aligned} R_{DFS}(A^*) = \sum_{x\in X} \frac{w_A(x)}{2}[(\mu^-_A(x) + \lambda_1(x)\pi^+_A(x)) \\ +(\mu^+_A(x) + \lambda_2(x)\pi^-_A(x))] \end{aligned} \tag{8}$$

If $\lambda(x) = 0$, we obtain:

$$R_{DFS}(A^*) = \sum_{x\in X} w_A(x)(\mu^+_A(x) + \lambda_2(x)\pi^-_A(x)) \tag{9}$$

Where:

$$w_A(x), \sum_{x\in X} w_A(x) = 1$$

APPLICATION TO SINGLE ATTRIBUTE DECISION MAKING

Suppose that there are eight candidates to be selected and that each candidate is given with the norm of interval-valued intuitionistic fuzzy sets as follows:

$$A = (M_A(x), N_A(x)) = ([\mu^-_A, \mu^+_A], [\nu^-_A, \nu^+_A])$$

And we get:

$$\begin{aligned} &A_1 = ([0.1,0.2],[0.3,0.4]), A_2 = ([0.1,0.2],[0.1,0.2]) \\ &A_3 = ([0.3,0.4],[0.3,0.4]), A_4 = ([0.3,0.4],[0.1,0.2]) \\ &A_5 = ([0.5,0.6],[0.3,0.4]), A_6 = ([0.5,0.6],[0.1,0.2]) \\ &A_7 = ([0.7,0.8],[0.1,0.2]), A_8 = ([0.7,0.8],[0,0.1]) \end{aligned}$$

As is well known that M_A (x) is the interval of membership degree and N_A (x) the interval of non-membership degree for each x. Therefore, if $\mu_A^- \leq \mu_B^-$, $\mu_A^+ \leq \mu_B^+$, $\nu_A^- \geq \nu_B^-$, $\nu_A^+ \geq \nu_B^+$, then B is superior than A, we define A = B or B = A and define A<B or B>A when A≠B.

For A_k (k = 1, 2, 3, 4, 5, 6, 7, 8), we have:

$$\begin{cases} A_1 < A_2 < A_4 < A_6 < A_7 < A_8, \\ A_1 < A_3 < A_5 < A_6 < A_7 < A_8 \end{cases} \quad (10)$$

From Eq. 7, we obtain some formulas as follows. And then we have Fig. 1.

Considering Fig. 1, we know that $A_1 < A_2 < A_4 < A_6 < A_7 < A_8$ and that $A_1 < A_3 < A_5 < A_6 < A_7 < A_8$ in Fig. 1. Thus, given λ(x) = 1, the membership function of DFS satisfy condition (10).

$$R_{DFS}(A_1^*) = 0.1 + 0.6\lambda_1, R_{DFS}(A_2^*) = 0.1 + 0.8\lambda_1,$$
$$R_{DFS}(A_3^*) = 0.3 + 0.4\lambda_1, R_{DFS}(A_4^*) = 0.3 + 0.6\lambda_1,$$
$$R_{DFS}(A_5^*) = 0.5 + 0.2\lambda_1, R_{DFS}(A_6^*) = 0.5 + 0.4\lambda_1,$$
$$R_{DFS}(A_7^*) = 0.7 + 0.2\lambda_1, R_{DFS}(A_7^*) = 0.7 + 0.3\lambda_1$$

From Eq. 9, we obtainFig. 2.

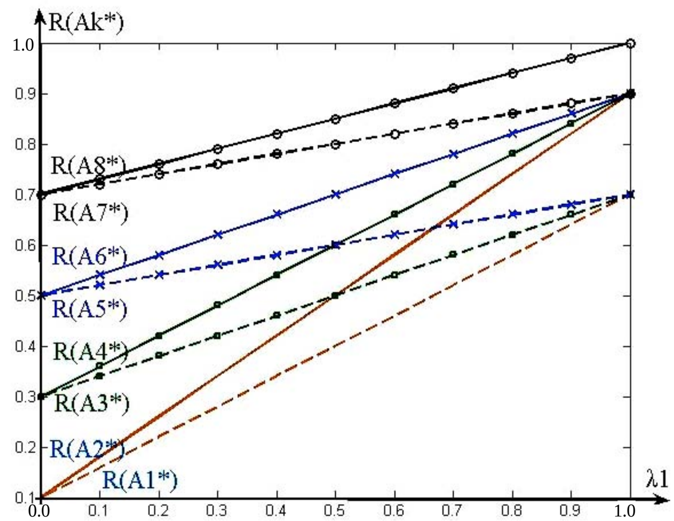

Fig. 1: Results of Eq. 7

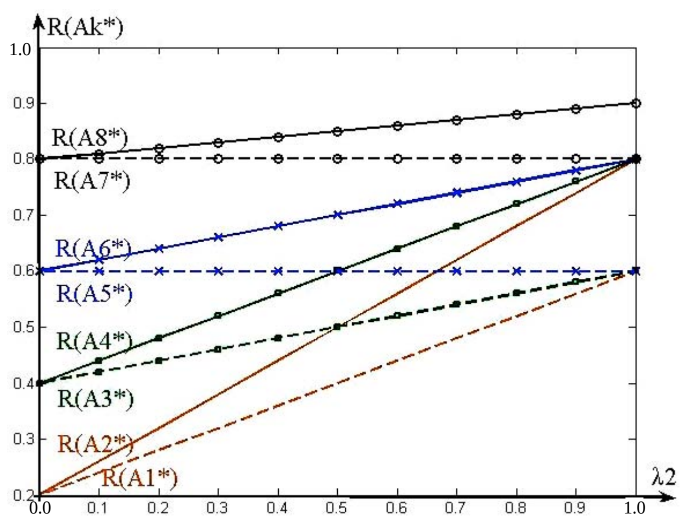

Fig. 2: Results of Eq. 9

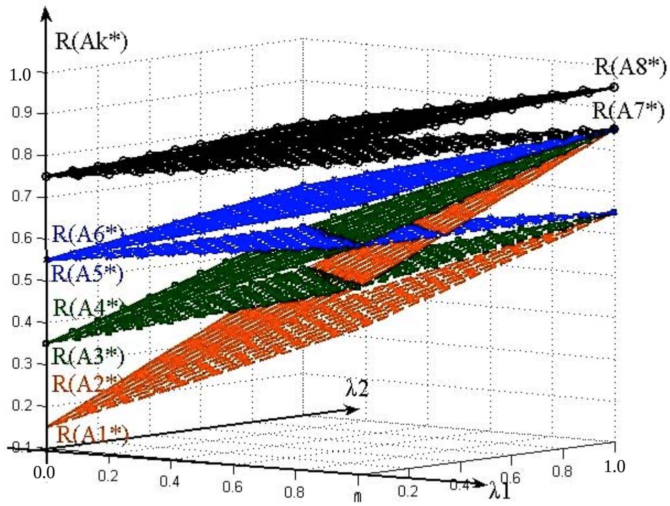

Fig. 3: Results of Eq. 8

$$R_{DFS}(A_1^*) = 0.2 + 0.4\lambda_2, R_{DFS}(A_2^*) = 0.2 + 0.6\lambda_2,$$
$$R_{DFS}(A_3^*) = 0.4 + 0.2\lambda_2, R_{DFS}(A_4^*) = 0.4 + 0.4\lambda_2,$$
$$R_{DFS}(A_5^*) = 0.6, R_{DFS}(A_6^*) = 0.6 + 0.2\lambda_2,$$
$$R_{DFS}(A_7^*) = 0.8, R_{DFS}(A_7^*) = 0.8 + 0.1\lambda_2$$

From Eq. 8, we obtain:

$$R_{DFS}(A_1^*) = 0.15 + 0.3\lambda_1 + 0.2\lambda_2,$$
$$R_{DFS}(A_2^*) = 0.15 + 0.4\lambda_1 + 0.3\lambda_2,$$
$$R_{DFS}(A_3^*) = 0.35 + 0.2\lambda_1 + 0.1\lambda_2,$$
$$R_{DFS}(A_4^*) = 0.35 + 0.3\lambda_1 + 0.2\lambda_2,$$
$$R_{DFS}(A_5^*) = 0.55 + 0.1\lambda_1,$$
$$R_{DFS}(A_6^*) = 0.55 + 0.2\lambda_1 + 0.1\lambda_2,$$
$$R_{DFS}(A_7^*) = 0.75 + 0.1\lambda_1,$$
$$R_{DFS}(A_8^*) = 0.75 + 0.15\lambda_1 + 0.05\lambda_2$$

And then we have Fig. 3.

From Fig. 2 and 3, we also obtain condition (10).

APPLICATION TO SUPPLIER SELECTION ON MULTIPLE ATTRIBUTE DECISION MAKING

The following numerical example is from the research presented by Kavita *et al*. (2009).

A high-technology manufacturing company desires to select a suitable material supplier to purchase the key components of new products. After preliminary screening, four candidates (A_1, A_2, A_3, A_4) remain for further evaluation. A committee of three decision makers D_1, D_2 and D_3, with weight vector W = 0.35, 0.35, 0.30, has been formed to select the most suitable supplier.

Four criteria are considered: x_1, Product quality; x_2, Relationship closeness; x_3, Delivery performance; x_4, Price.

The proposed method is currently applied to solve this problem, the computational procedure is as follows: The decision makers D_k (k = 1, 2, 3) compare each pair of the criteria's x_i (i = 1, 2, 3, 4) and construct the following three interval-valued intuitionistic fuzzy judgment matrices.

In their study, Kavita *et al.* (2009) obtain the preference order of alternatives is $A_1>A\ >_2A\ >A_4$ 3
according to a multi-criteria interval-valued intuitionistic fuzzy group decision making method based on the technique for order preference by similarity to ideal solution method (TOPSIS), where $A_i>A_j$ means that A_i is superior than A_j:

$$D_1 = \begin{bmatrix} A_k \backslash X_i & x_1 & x_2 & x_3 & x_4 \\ A_1 & ([0.5,0.5],[0.5,0.5]) & ([0.6,0.7],[0.1,0.2]) & ([0.5,0.6],[0.2,0.3]) & ([0.3,0.5],[0.2,0.4]) \\ A_w & ([0.1,0.2],[0.6,0.7]) & ([0.5,0.5],[0.5,0.5]) & ([0.4,0.6],[0.1,0.2]) & ([0.6,0.7],[0.1,0.3]) \\ A_3 & ([0.2,0.3],[0.5,0.6]) & ([0.1,0.2],[0.4,0.6]) & ([0.5,0.5],[0.5,0.5]) & ([0.3,0.4],[0.5,0.6]) \\ A_4 & ([0.2,0.4],[0.3,0.5]) & ([0.1,0.3],[0.6,0.7]) & ([0.5,0.6],[0.3,0.4]) & ([0.5,0.5],[0.5,0.5]) \end{bmatrix}$$

$$D_2 = \begin{bmatrix} A_k \backslash X_i & x_1 & x_2 & x_3 & x_4 \\ A_1 & ([0.5,0.5],[0.5,0.5]) & ([0.2,0.3],[0.5,0.6]) & ([0.5,0.7],[0.1,0.2]) & ([0.2,0.4],[0.1,0.3]) \\ A_w & ([0.5,0.6],[0.2,0.3]) & ([0.5,0.5],[0.5,0.5]) & ([0.5,0.8],[0.1,0.2]) & ([0.3,0.6],[0.2,0.3]) \\ A_3 & ([0.1,0.2],[0.5,0.7]) & ([0.1,0.2],[0.5,0.8]) & ([0.5,0.5],[0.5,0.5]) & ([0.4,0.6],[0.1,0.4]) \\ A_4 & ([0.1,0.3],[0.2,0.4]) & ([0.2,0.3],[0.3,0.6]) & ([0.1,0.4],[0.4,0.6]) & ([0.5,0.5],[0.5,0.5]) \end{bmatrix}$$

$$D_3 = \begin{bmatrix} A_k \backslash X_i & x_1 & x_2 & x_3 & x_4 \\ A_1 & ([0.5,0.5],[0.5,0.5]) & ([0.4,0.5],[0.2,0.3]) & ([0.6,0.7],[0.1,0.2]) & ([0.5,0.7],[0.2,0.3]) \\ A_w & ([0.2,0.3],[0.4,0.5]) & ([0.5,0.5],[0.5,0.5]) & ([0.5,0.6],[0.2,0.4]) & ([0.7,0.8],[0.1,0.2]) \\ A_3 & ([0.1,0.2],[0.6,0.7]) & ([0.2,0.4],[0.5,0.6]) & ([0.5,0.5],[0.5,0.5]) & ([0.6,0.7],[0.1,0.3]) \\ A_4 & ([0.2,0.3],[0.5,0.7]) & ([0.1,0.2],[0.7,0.8]) & ([0.1,0.3],[0.6,0.7]) & ([0.5,0.5],[0.5,0.5]) \end{bmatrix}$$

Assume that the weight vector of the criteria is $W_A(x) = (0.25, 0.25, 0.25, 0.25)$ and that $\lambda_1(x) = \lambda_1$, $\lambda_2(x) = \lambda_2$ for each criteria $x \in \{x_i | i = 1, 2, 3, 4\}$.

From Eq. 7, we have the following equations and Fig. 4:

$$R_{DFS}(A_1^*) = 0.43875 + 0.29375 \times \lambda_1,$$
$$R_{DFS}(A_2^*) = 0.44 + 0.26875 \times \lambda_1,$$
$$R_{DFS}(A_3^*) = 0.2975 + 0.26875 \times \lambda_1,$$
$$R_{DFS}(A_4^*) = 0.26 + 0.29625 \times \lambda_1$$

From Fig. 4, we have Table 1.

From Eq. 9, we have:

$$R_{DFS}(A_1^*) = 0.5475 + 0.0925 \times \lambda_2,$$
$$R_{DFS}(A_2^*) = 0.55875 + 0.05875 \times \lambda_2,$$
$$R_{DFS}(A_3^*) = 0.38875 + 0.0425 \times \lambda_2,$$
$$R_{DFS}(A_4^*) = 0.38625 + 0.04375 \times \lambda_2$$

And then we have Fig. 5 and Table 2.

From Eq. 8, we have:

$$R_{DFS}(A_1^*) = 0.493125 + 0.146875 \times \lambda_1 + 0.04625 \times \lambda_2,$$
$$R_{DFS}(A_2^*) = 0.499375 + 0.134375 \times \lambda_1 + 0.029375 \times \lambda_2,$$
$$R_{DFS}(A_3^*) = 0.343125 + 0.134375 \times \lambda_1 + 0.02125 \times \lambda_2,$$
$$R_{DFS}(A_4^*) = 0.323125 + 0.148125 \times \lambda_1 + 0.021875 \times \lambda_2$$

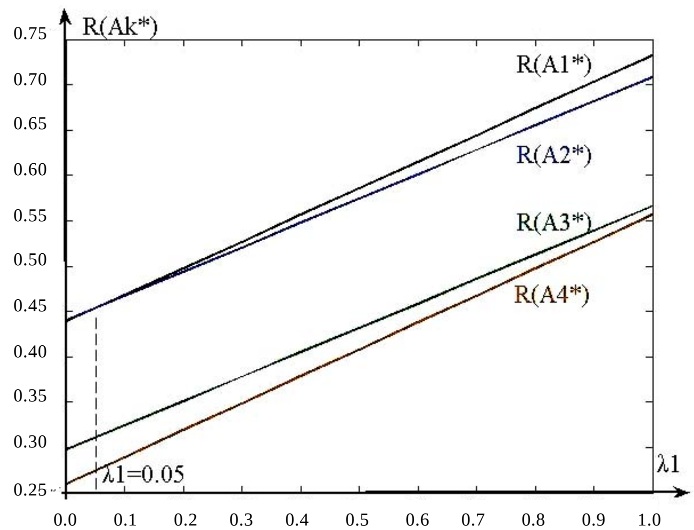

Fig. 4: Ranking functions of Eq. 7

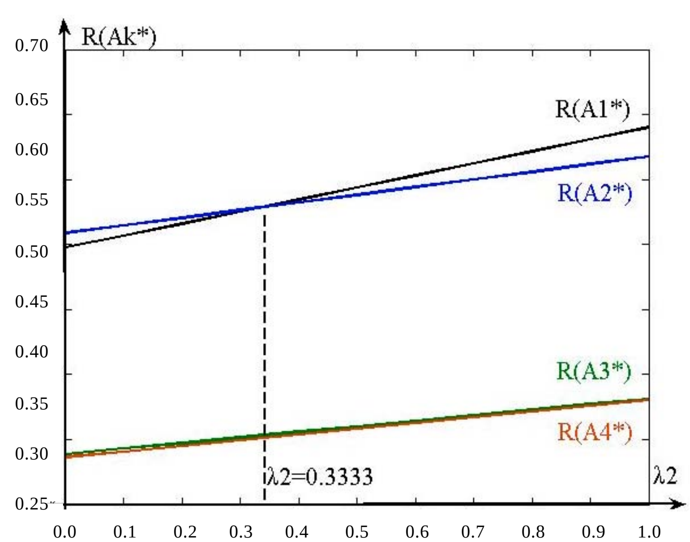

Fig. 5: The Ranking functions of Eq. 9

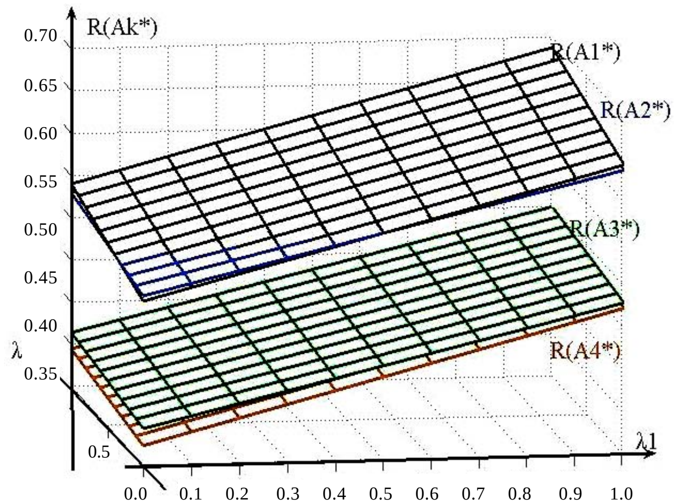

Fig. 6: Ranking functions of Eq .8

Table 1: Preference order of alternatives from Eq. 7

λ1	Preference order of alternatives is	Optimal decision making is
$0 \le \lambda_1 < 0.05$	$A_2 > A_1 > A_3 > A_4$	A_2
$0.05 < \lambda_1 \le 1$	$A_1 > A_2 > A_3 > A_4$	A_1

Table 2: Preference order of alternatives from Eq. 9

λ2	Preference order of alternatives is	Optimal decision making is
$0 \le \lambda_2 < 0.3333$	$A_2 > A_1 > A_3 > A_4$	A_2
$0.3333 < \lambda_2 \le 1$	$A_1 > A_2 > A_3 > A_4$	A_1

Table 3: The preference order of alternatives from Eq. 8

λ_1 and λ_2	Preference order of alternatives is	Optimal decision making is
$0.00625-0.0125\lambda_1-0.016875\lambda 2<0$	$A_2 > A_1 > A_3 > A_4$	A_2
$0.00625-0.0125\lambda_1-0.016875\lambda_2>0$	$A_1 > A_2 > A_3 > A_4$	A_1

$$\bar{D} = \begin{bmatrix} A_i \backslash X_j & x_1 & x_2 & x_3 & x_4 \\ A_1 & ([0.5,0.5],[0.5,0.5]) & ([0.4,0.5],[0.27,0.37]) & ([0.53,0.665],[0.135,0.235]) & ([0.325,0.525],[0.165,0.335]) \\ A_2 & ([0.27,0.37],[0.4,0.5]) & ([0.5,0.5],[0.5,0.5]) & ([0.465,0.67],[0.13,0.26]) & ([0.525,0.695],[0.135,0.27]) \\ A_3 & ([0.135,0.235],[0.53,0.665]) & ([0.13,0.26],[0.465,0.67]) & ([0.5,0.5],[0.5,0.5]) & ([0.425,0.56],[0.24,0.44]) \\ A_4 & ([0.165,0.335],[0.325,0.525]) & ([0.135,0.27],[0.525,0.695]) & ([0.24,0.44],[0.425,0.56]) & ([0.5,0.5],[0.5,0.5]) \end{bmatrix}$$

And then we have Fig. 6.

From Figure 6, we have Table 3.

From Fig. 4-6 and from Table 1-3, we know that $A_1 > A_2$ in most cases for parameter λ_i (i = 1, 2) and we also obtain $A_1 > A_3 > A_4$ and $A_2 > A_3 > A_4$ for $\lambda \in [0, 1]$ and $\lambda_2 \in [0, 1]$. Therefore, A_1 should be the optimal decision, which is the same as the results from Kavita's method (Kavita *et al*., 2009).

We can also construct the average matrix of all the decision makers according to their weights and get a matrix of average value $\bar{D}$ as follows.

Considering the realistic meaning of interval-valued intuitionistic fuzzy sets, we draw a conclusion.

For x_1, x_2 and x_3, A_1 should be the optimal choice. For x_4, the membership-degree interval of A_1 is lower than the others. Thus, A_1 is better than A_2 for x_1, x_2 and x_3, but A_2 is better than A_1 for x_4. In summary, we should select A_1 in practice. As for A_3 and A_4, A_4 is better than A_3 for x_1, but A_3 is better than A_4 for x_2, x_3 and x_4. Thus, the result should satisfy $A_3 > A_4$ in general. However, using the traditional IVIFS TOPSIS method (Kavita *et al*., 2009). Tthe result is $A_4 > A_3$ which is different from the general knowledge analyzed above.

Though Kavita *et al*. (2009) obtain the similar result using a TOPSIS method based on interval-valued intuitionistic fuzzy sets, the operation process of their method is rather complex. In this study, we present a dynamic fuzzy decision making method, which is simpler than Kavita's method according to the computational process. And for A_3 and A_4, DFS method is better than TOPSIS method. Moreover, we can control the output by adjusting the parameters according to the actual demand.

CONCLUSION

We present a novel dynamic fuzzy decision making method derived from interval-valued intuitionistic fuzzy sets method. And we apply the novel dynamic fuzzy sets method to single attribute decision making and supplier selection based on multiple attribute group decision making. Simulation results show that the DFS method is simpler and more comprehensive than the traditional IVIFS method.

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APPENDIX

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