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METHODOLOGIES AND APPLICATION

D-AHP method with different credibility of information

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Abstract

Multi-criteria decision making (MCDM) has attracted wide interest due to its extensive applications in practice. In our previous study, a method called D-AHP (AHP method extended by D numbers preference relation) was proposed to study the MCDM problems based on a D numbers extended fuzzy preference relation, and a solution for the D-AHP method has been given to obtain the weights and ranking of alternatives from the decision data, in which the results obtained by using the D-AHP method are influenced by the credibility of information. However, in previous study the impact of information's credibility on the results is not sufficiently investigated, which becomes an unsolved issue in the D-AHP. In this paper, we focus on the credibility of information within the D-AHP method and study its impact on the results of a MCDM problem. Information with different credibilities including high, medium and low, respectively, is taken into consideration. The results show that the credibility of information in the D-AHP method slightly impacts the ranking of alternatives, but the priority weights of alternatives are influenced in a relatively obvious extent.

Keywords D-AHP · D numbers preference relation · Fuzzy preference relation · Dempster–Shafer theory · Multi-criteria decision making

1 Introduction

Multi-criteria decision making (MCDM) has become a hot research issue for a long time (Chen et al. 1992; Ribeiro 1996; Wei 2008; Jiang et al. 2018). Up to now, various methods and approaches have been developed to study this problem, such as TOPSIS (García-Cascales and Lamata 2012; Tsaur 2011), VIKOR (Opricovic and Tzeng 2004, 2007; Sayadi et al. 2009), evidential reasoning-based approach (Yager 1992; Deng and Jiang 2018; Xu and Deng 2018), and analytic hierarchy process (AHP) (Saaty 1980), fuzzy-based method (Zhang et al. 2017; Xu and Yager 2008; Fei et al. 2017; Nie et al. 2011), etc. (Jiang et al. 2017a; Zheng and Deng 2018b). Besides, game theory, as a tool to study agent's behaviors in competitive environment (Wang et al. 2017, 2016; Deng et al. 2016; Xu et al. 2018), is also widely used in the field of MCDM (Aplak and Türkbey 2013; Peldschus and Zavadskas 2005; Aplak and Sogut 2013; Yang et al. 2013; Liu et al. 2017a; Kang et al. 2017). Among them, the AHP method has attracted widely attention due to its ability in uniting both qualitative and quantitative factors in decision-making process. In the classical AHP model, the relative importance between elements, also called preference relation between elements, is represented in a pairwise comparison matrix.

Generally, the multiplicative preference relation (Saaty 1980) satisfying $a_{ij} \times a_{ji} = 1$ is often employed in the AHP method. Meanwhile, other types of preference relations are also existing. One is called fuzzy preference relation satisfying $r_{ij} + r_{ji} = 1$. A fuzzy preference relation (Tanino 1984; Herrera-Viedma et al. 2004, 2007; Xu 2007) provides another way to construct a decision matrix of pairwise comparisons based on linguistic values given by experts. However, the conventional fuzzy preference relation is on the basis of complete and certain information. It is unable to deal with the cases involving incompleteness and uncertainty. In order to overcome this deficiency, in reference (Deng et al. 2014b) a concept of D numbers preference relation was proposed which extends the fuzzy preference relation by using D numbers, where the tool of D numbers (Deng et al. 2014a, b; Deng 2012) provides a new representation to express the

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uncertain information by extending Dempster–Shafer theory (Dempster 1967; Shafer 1976; Denoeux 2013; Antoine et al. 2014; Zheng et al. 2017; Zheng and Deng 2018a; Yager 2014; Yang and Xu 2013; Yager and Liu 2008). Based on the concept of D numbers preference relation, a D-AHP method (Deng et al. 2014b) has been proposed for MCDM problems, and the D-AHP method extends the traditional AHP method in theory.

In the proposed D-AHP method, the derived results about the ranking and priority weights of alternatives are impacted by the credibility of providing information. A parameter λ is used to express the credibility of information, and its value is associated with the cognitive ability of experts. If the comparison information used in the decision-making process is provided by an authoritative expert, λ will take a smaller value. If the comparison information comes from an expert whose judgment is with low belief, λ takes a higher value. As suggested in Deng et al. (2014b), a feasible scheme is shown as follows.

$$\lambda = \begin{cases} \lceil \underline{\lambda} \rceil, & \text{The information is with high credibility} \\ n, & \text{The information is with medium credibility} \\ n^2/2, & \text{The information is with low credibility} \end{cases} \tag{1}$$

where $\underline{\lambda}$ represents lower bound of λ, and $\lceil \underline{\lambda} \rceil = \min\{k \in \mathbb{Z} | k \geqslant \underline{\lambda}\}$, and n is the number of alternatives. For instance, $\lceil \underline{\lambda} \rceil = 2$ if $\underline{\lambda} = 1.58$. In previous study (Deng et al. 2014b), the D-AHP method has been successfully used to solve a supplier selection problem, but the credibility of providing information is not further and deeply studied. In this paper, the credibility of information is focused to investigate its impact on the decision-making results when applying the D-AHP method to a MCDM problem. Three cases, namely information with high credibility, medium credibility and low credibility, are taken into consideration, respectively. The results show that the credibility of information slightly impacts the ranking of alternatives, but the priority weights of alternatives are influenced in a relatively obvious degree. The explanation and reasonability for the results are well displayed in this paper.

The remainder of this paper is organized as follows. A brief introduction about D numbers is presented in Sect. 2. Then the D-AHP method is given in Sect. 3. After that, a case study considering the credibility of information in the D-AHP method is presented in Sect. 4. Finally, conclusions are given in Sect. 5.

2 D numbers

The tool of D numbers (Deng et al. 2014a, b; Deng 2012) is a new representation for uncertain information, which can be seen as an extension of basic probability assignment (BPA) in Dempster–Shafer theory (Dempster 1967; Shafer 1976; Jiang and Zhan 2017) for uncertainty modeling and handling (Jiang and Wang 2017; Deng et al. 2017; Zhang et al. 2018). At present, it has been used in some fields, for example supplier selection (Deng et al. 2014b), environmental impact assessment (Deng et al. 2014a), failure mode and effects analysis (Liu et al. 2014, 2018; Jiang et al. 2017b). D numbers overcome a few of existing deficiencies (i.e., exclusiveness hypothesis and completeness constraint; refer to Deng et al. 2014a, b for more details) in Dempster–Shafer theory and is very effective in representing various types of uncertainties. Some basic concepts about D numbers are given as follows.

Definition 1 Let Θ be a nonempty set $\Theta = \{F_1, F_2, \ldots, F_N\}$ satisfying $F_i \neq F_j$ if $i \neq j, \forall i, j = \{1, \ldots, N\}$, a D number is a mapping formulated by

$$D : 2^{\Theta} \to [0, 1] \tag{2}$$

with

$$\sum_{B \subseteq \Theta} D(B) \leq 1 \quad \text{and} \quad D(\emptyset) = 0 \tag{3}$$

where $\emptyset$ is the empty set and B is a subset of Θ.

If $\sum_{B \subseteq \Theta} D(B) = 1$, the information expressed by the D number is said to be complete; if $\sum_{B \subseteq \Theta} D(B) < 1$, the information is said to be incomplete.

For a discrete set $\Theta = \{b_1, b_2, \ldots, b_i, \ldots, b_n\}$, where $b_i \in R$ and $b_i \neq b_j$ if $i \neq j$, a special form of D numbers can be expressed by Deng et al. (2014a, b)

$$D(\{b_1\}) = v_1, D(\{b_2\}) = v_2, \ldots, D(\{b_i\}) = v_i, \ldots, D(\{b_n\}) = v_n \tag{4}$$

or simply denoted as $D = \{(b_1, v_1), (b_2, v_2), \ldots, (b_i, v_i), \ldots, (b_n, v_n)\}$, where $v_i > 0$ and $\sum_{i=1}^{n} v_i \leq 1$. Some properties of this form of D numbers are introduced as follows.

Remark 1 Permutation invariability. If there are two D numbers that $D_1 = \{(b_1, v_1), \ldots, (b_i, v_i), \ldots, (b_n, v_n)\}$ and $D_2 = \{(b_n, v_n), \ldots, (b_i, v_i), \ldots, (b_1, v_1)\}$, then $D_1 \Leftrightarrow D_2$.

Remark 2 For a D number $D = \{(b_1, v_1), (b_2, v_2), \ldots, (b_i, v_i), \ldots, (b_n, v_n)\}$, the integration representation of D is defined as

$$I(D) = \sum_{i=1}^{n} b_i v_i \tag{5}$$

where $b_i \in R$, $v_i > 0$ and $\sum_{i=1}^{n} v_i \leq 1$. For the sake of simplification, the integration representation of a D number is called its I value.

3 D-AHP method

3.1 D numbers preference relation

Preference relation (Xu 2007) which is usually denoted as pairwise comparison matrix is a classical means to express expert's subjective knowledge. Generally, there are two types of preference relations: multiplicative preference relation satisfying $a_{ij} \times a_{ji} = 1$ and additive preference relation, also called fuzzy preference relation, satisfying $r_{ij} + r_{ji} = 1$. A reciprocal fuzzy preference relation can be conveniently represented by an $n \times n$ matrix $R = [r_{ij}]_{n\times n}$, being $r_{ij} = \mu_R(A_i, A_j) \forall i, j \in \{1, 2, \ldots, n\}$, namely (Tanino 1984; Herrera-Viedma et al. 2004, 2007)

$$R = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \cdots & A_n \end{array} \\ \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \cdots & r_{nn} \end{bmatrix} \end{array} \tag{6}$$

where (1) $r_{ij} \geq 0$; (2) $r_{ij} + r_{ji} = 1$, $\forall i, j \in \{1, 2, \ldots, n\}$; (3) $r_{ii} = 0.5$, $\forall i \in \{1, 2, \ldots, n\}$. r_{ij} denotes the preference degree of alternative A_i over alternative A_j, where $r_{ij} = 0$ means that A_j is absolutely preferred to A_i, $r_{ij} < 0.5$ that A_j is preferred to A_i to some degree, $r_{ij} = 0.5$ that there is indifferent between A_i and A_j. On the contrary, $r_{ij} > 0.5$ means that A_i is preferred to A_j to some degree, $r_{ij} = 1$ implies that A_i is absolutely preferred to A_j.

However, the original fuzzy preference relation can be only constructed on the basis of complete and certain information. It is unable to deal with the cases that involve incomplete and uncertain information. In order to overcome the deficiency, in the literature (Deng et al. 2014b) we proposed the concept of D numbers preference relations which extends the fuzzy preference relations by using D numbers. The D numbers preference relation is formulated by

$$R_D = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \cdots & A_n \end{array} \\ \begin{bmatrix} D_{11} & D_{12} & \cdots & D_{1n} \\ D_{21} & D_{22} & \cdots & D_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ D_{n1} & D_{n2} & \cdots & D_{nn} \end{bmatrix} \end{array} \tag{7}$$

where $D_{ij} = \{(b_{ij}^1, v_{ij}^1), (b_{ij}^2, v_{ij}^2), \ldots, (b_{ij}^p, v_{ij}^p), \cdots\}$, $D_{ji} = \neg D_{ij} = \{(1-b_{ij}^1, v_{ij}^1), (1-b_{ij}^2, v_{ij}^2), \ldots, (1-b_{ij}^p, v_{ij}^p), \cdots\}$, $\forall i, j \in \{1, 2, \ldots, n\}$, and $b_{ij}^p \in [0, 1]$, $v_{ij}^p > 0$, $\sum_p v_{ij}^p = 1$. Obviously, $D_{ii} = \{(0.5, 1.0)\}$ $\forall i \in \{1, 2, \ldots, n\}$ in R_D. Because the D numbers preference relation can be represented in the form of matrix, herein, the corresponding matrix is called D numbers preference matrix, abbreviated as D matrix.

3.2 Solution for a D numbers preference relation

Once a D numbers preference relation about alternatives has been constructed, a key problem is how to obtain the ranking and priority weights of alternatives based on the D numbers preference relation. In Deng et al. (2014b), we studied the solution for D numbers preference relation. The procedure of the solution is shown in Fig. 1.

Step 1 At first, the D numbers preference relation R_D is converted to an I values matrix R_I by using Eq.(5).
Step 2 At second, let us construct a probability matrix R_p based on R_I, where R_p represents the preference probability between each pair of alternatives.
Step 3 At third, in terms of R_p, a triangular probability matrix R_p^T is derived, with the assist of local information if necessary. Based on R_p^T, the ranking of alternatives can be obtained.
Step 4 At fourth, a triangulated I values matrix R_I^T is generated based on R_I and R_p^T; then, the weights of alternatives can finally calculated by means of R_I^T.

Please refer to the literature (Deng et al. 2014b) for more details. In the following, a numerical example is given to simply exhibit this procedure.

Example 1 Assume there are four proposals P_1, P_2, P_3, P_4 for building a power station. The pairwise comparisons among the four proposals are given in Table 1.

In order to obtain the ranking of all proposals and priority weigh of each one, the solution shown in Fig. 1 is utilized. Here the detailed process is omitted, but some important intermediate outcomes are given as follows.

$$R_I = \begin{bmatrix} 0.50 & 0.80 & 0.60 & 0.55 \\ 0.20 & 0.50 & 0.80 & 0.48 \\ 0.40 & 0.20 & 0.50 & 0.90 \\ 0.45 & 0.12 & 0.10 & 0.50 \end{bmatrix} \tag{8}$$

$$R_p = \begin{bmatrix} 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0.95 \\ 0 & 0 & 0 & 1 \\ 0 & 0.05 & 0 & 0 \end{bmatrix} \tag{9}$$

$$R_p^T = \begin{bmatrix} 0 & 1 & 1 & 1 \\ 0 & 0 & 1 & 0.95 \\ 0 & 0 & 0 & 1 \\ 0 & 0.05 & 0 & 0 \end{bmatrix} \tag{10}$$

$$R_I^T = \begin{bmatrix} 0.50 & 0.80 & 0.60 & 0.55 \\ 0.20 & 0.50 & 0.80 & 0.68 \\ 0.40 & 0.20 & 0.50 & 0.90 \\ 0.45 & 0.32 & 0.10 & 0.50 \end{bmatrix} \tag{11}$$

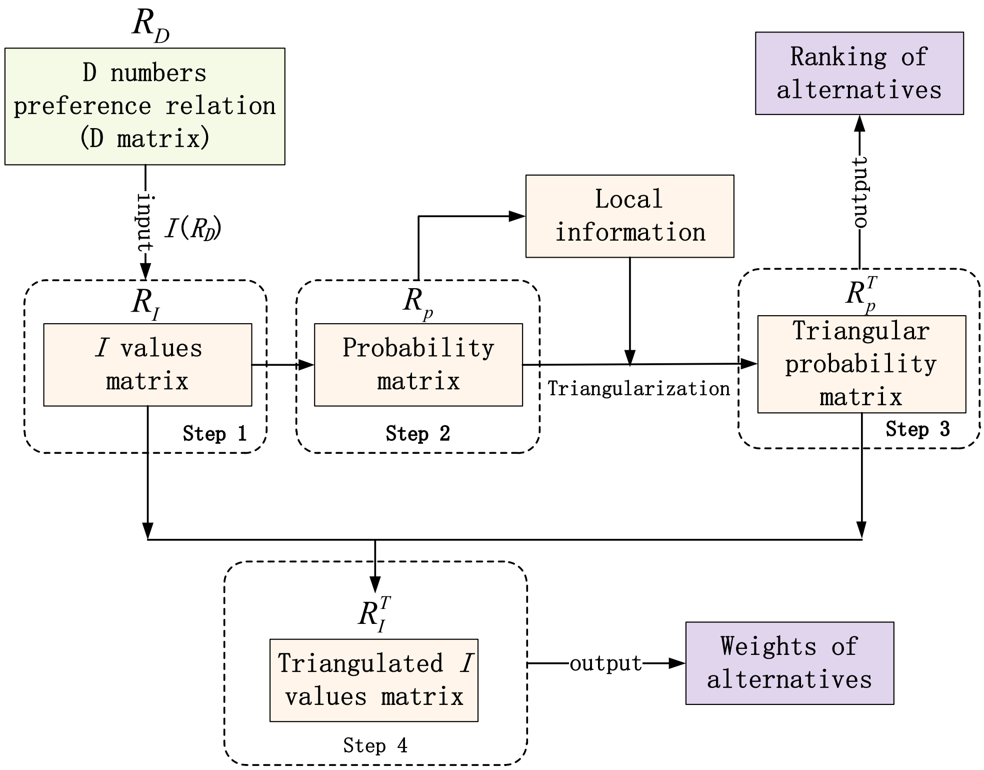

Fig. 1 Procedure to obtain the ranking and priority weights of alternatives based on a D numbers preference relation (Deng et al. 2014b)

Table 1 Pairwise comparisons among four proposals in the form of D numbers preference relation

	P_1	P_2	P_3	P_4
P_1	{(0.5, 1.0)}	{(0.8, 1.0)}	{(0.6, 1.0)}	{(0.5, 0.5), (0.6, 0.5)}
P_2	{(0.2, 1.0)}	{(0.5, 1.0)}	{(0.8, 1.0)}	{(0.8, 0.6)}
P_3	{(0.4, 1.0)}	{(0.2, 1.0)}	{(0.5, 1.0)}	{(0.9, 1.0)}
P_4	{(0.5, 0.5), (0.4, 0.5)}	{(0.2, 0.6)}	{(0.1, 1.0)}	{(0.5, 1.0)}

According to R_p^T, the ranking of proposals can be derived: $P_1 \succ P_2 \succ P_3 \succ P_4$. In R_I^T, the elements above and alongside the main diagonal, namely (0.8, 0.8, 0.9), indicate the weight relationship of proposals. Because $R_I^T(1,2) = 0.8$, $R_I^T(2,3) = 0.8$, $R_I^T(3,4) = 0.9$, the weights of proposals, indicated by w_1, w_2, w_3 and w_4, meet the following equations:

$$\begin{cases} \lambda(w_1 - w_2) = 0.8 - 0.5 \\ \lambda(w_2 - w_3) = 0.8 - 0.5 \\ \lambda(w_3 - w_4) = 0.9 - 0.5 \\ w_1 + w_2 + w_3 + w_4 = 1 \\ \lambda > 0 \\ w_i \geq 0, \quad \forall i \in \{1, 2, 3, 4\} \end{cases} \tag{12}$$

By solving Eq.(12), we have

$$\begin{cases} w_1 = 1/4 + 0.475/\lambda \\ w_2 = 1/4 + 0.175/\lambda \\ w_3 = 1/4 - 0.125/\lambda \\ w_4 = 1/4 - 0.525/\lambda \end{cases}, \quad \lambda \in [2.1, +\infty) \tag{13}$$

where parameter λ expresses the credibility of information. If the comparison information is provided by an authoritative expert, λ takes a smaller value; if the comparison information comes from an expert whose judgment is with low belief, λ takes a higher value. The decline of λ means the decrease in expert's cognitive ability to slight difference, which will lead that the weights of proposals are gradually closing to each others. Figure 2 shows the weight of each proposal with the change in λ. It is easy to find that the difference among weights of proposals declines with the increase in λ. In Deng et al. (2014b), a scheme is suggested to determine the value of λ as follows.

$$\lambda = \begin{cases} \lceil \underline{\lambda} \rceil, & \text{The information is with high credibility} \\ n, & \text{The information is with medium credibility} \\ n^2/2, & \text{The information is with low credibility} \end{cases} \tag{14}$$

Based on this scheme, the weights of these proposals are obtained, as shown in Table 2.

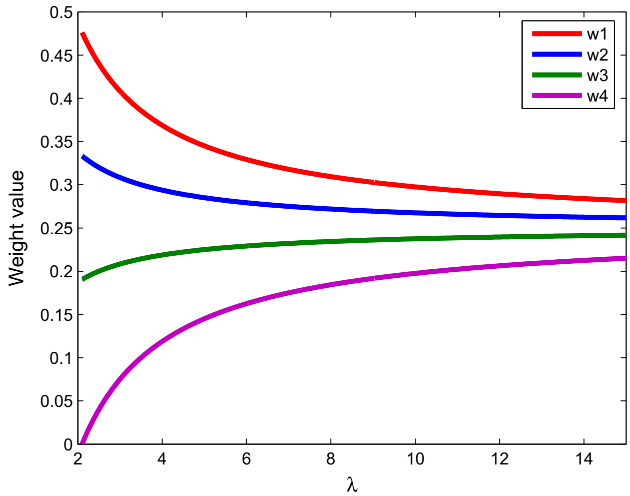

Fig. 2 Weights of proposals with the change in λ

Table 2 Weights and ranking of proposals in Example 1

Proposals	Weights (different credibility of information)				Ranking
	High	Medium	Low	Range	
P_1	0.408	0.369	0.309	(0.250, 0.476]	1
P_2	0.308	0.294	0.272	(0.250, 0.333]	2
P_3	0.208	0.219	0.234	[0.190, 0.250)	3
P_4	0.075	0.119	0.184	[0.000, 0.250)	4

3.3 Hierarchical structure of D-AHP method

Based on the concept of D numbers preference relation, in Deng et al. (2014b) a D-AHP method has been proposed to extend the traditional AHP method. The hierarchical structure of D-AHP method is shown in Fig. 3. In the D-AHP, the critical point, obtaining the priority weights of alternatives based on the D numbers preference relation in each hierarchy, is solved by using the solution shown in Sect. 3.2. The determination of final priority weight of each alternative is a recursive integration layer by layer, as shown in Table 3.

4 Case study considering the credibility of information

As mentioned above, in the D-AHP the critical issue is to calculate the priority weights in each D numbers preference relation. But the setting of information's credibility, i.e., λ, has an impact on the results within the framework of D-AHP method. In previous study, the sensitivity analysis of λ is not discussed. In this section, we will use an illustrative example to exhibit the impact of information's credibility on the final outcomes.

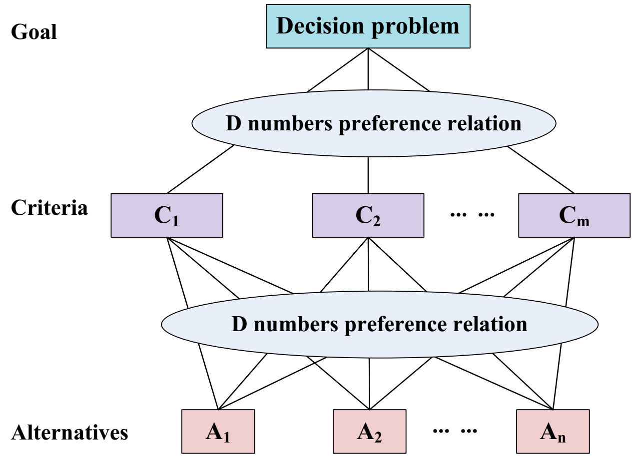

Fig. 3 Hierarchical structure of D-AHP method (Deng et al. 2014b)

Table 3 Integration of each level's weights in D-AHP (Deng et al. 2014b)

Alternatives	Criteria				Alternatives' weights for the decision problem
	C_1	C_2	$\cdots$	C_m	
	c_1	c_2	$\cdots$	c_m	
A_1	a_{11}	a_{12}	$\ldots$	a_{1m}	$w_1 = \sum_{i=1}^{m} c_i a_{1i}$
A_1	a_{11}	a_{12}	$\ldots$	a_{1m}	$w_1 = \sum_{i=1}^{m} c_i a_{1i}$
A_2	a_{21}	a_{22}	$\ldots$	a_{2m}	$w_2 = \sum_{i=1}^{m} c_i a_{2i}$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
A_n	a_{n1}	a_{n2}	$\ldots$	a_{nm}	$w_n = \sum_{i=1}^{m} c_i a_{ni}$

In the literature, Chen and Chao (2012) gave an example of supplier selection about an electronic company in southern Taiwan. In that paper, the authors have given detailed data about the example; please refer to Chen and Chao (2012) to get the data. In the example, there are four alternatives: X_1, X_2, X_3 and X_4. The structure of multi-criteria for supplier selection is displayed in Fig. 4. Based on those given data in Chen and Chao (2012), the ranking and priority weights of alternatives can be obtained by using the D-AHP method under different credibility of information, as shown in Tables 4, 5 and 6.

From the tables, the ranking of alternatives is

$$X_3 \underset{0.072}{\succ} X_1 \underset{0.153}{\succ} X_2 \underset{0.030}{\succ} X_4, \tag{15}$$

if the information is considered to be highly credible. The ranking is

$$X_3 \underset{0.0}{\succ} X_1 \underset{0.061}{\succ} X_2 \underset{0.014}{\succ} X_4, \tag{16}$$

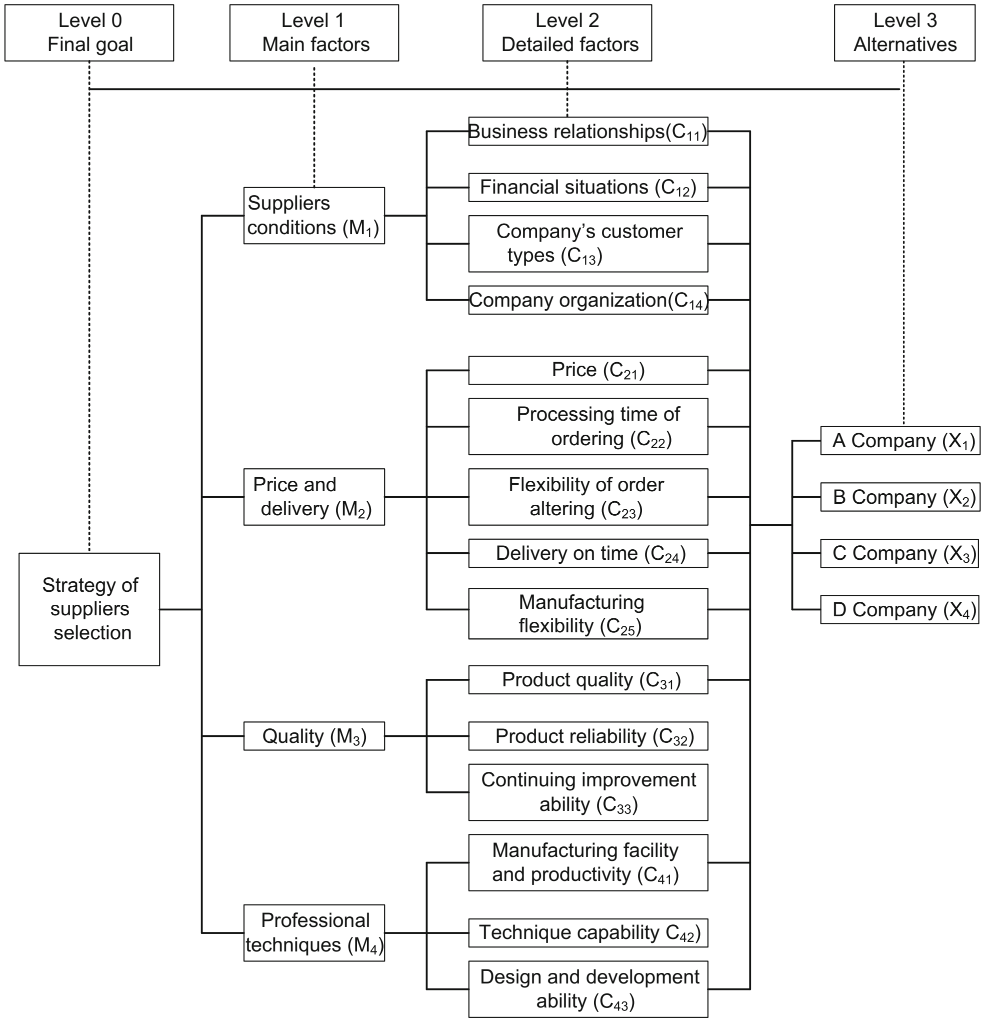

Fig. 4 Structure of multi-criteria for supplier selection (Chen and Chao 2012)

if the information is considered to be moderately credible. The ranking is

$$X_1 \underset{0.002}{\succ} X_3 \underset{0.030}{\succ} X_2 \underset{0.007}{\succ} X_4, \tag{17}$$

if the information is considered to have low credibility. As can be found from these results, the rankings of alternatives are basically same in the situations of high credibility and medium credibility. In these two situations, the best alternative is X_3, and the worst alternative is X_4. Compared with the situation of information with medium credibility which yields two best alternatives X_3 and X_1, the information with high credibility is more effective in distinguishing X_3 and X_1, which reflects the assumption that high credibility shows the information has better cognitive ability. Besides, the differences among the obtained weights are relatively big in the two situations. The ranking of alternatives given by high or medium credibility is the same with the results given in the literature (Chen and Chao 2012) that is $X_3 \underset{0.01}{\succ} X_1 \underset{0.11}{\succ} X_2 \underset{0.03}{\succ} X_4$.

Now let us consider the situation of low credibility. In the situation, superficially the best alternative is X_1 and the worst alternative is X_4. But specifically, because their weights are $w_1 = 0.268$, $w_3 = 0.266$, $w_2 = 0.236$ and $w_4 = 0.229$, respectively, the gap between w_1 and w_3 is very small, i.e., $w_1 - w_3 = 0.002$. Also, the gap between w_2 and w_4 is still very small, i.e., $w_2 - w_4 = 0.007$. Conversely, the gap between w_3 and w_2 is relatively big, i.e., $w_3 - w_2 = 0.030$. So, these alternatives are actually divided into two groups, namely superior suppliers $\{X_1, X_3\}$ and inferior suppliers $\{X_2, X_4\}$, when the credibility of information is low. From this point of view, qualitatively the result in the situation of low credibility is basically consistent with that in the situations of medium credibility and high credibility.

Such sensitivity analysis shows that as a whole these results, derived from the information whether it is high or medium or low credibility, are reasonable. And the results are

Table 4 Result of D-AHP method when the information is with high credibility

Main criteria		Sub-criteria		Alternatives			
M_i		C_{ij}		X_1	X_2	X_3	X_4
M_1	0.18	C_{11}	0.1975	0.3662	0.2412	0.2762	0.1162
		C_{12}	0.5075	0.3575	0.0075	0.1675	0.4675
		C_{13}	0.2575	0.355	0.205	0.33	0.11
		C_{14}	0.0375	0.4875	0.0775	0.3775	0.0575
M_2	0.48	C_{21}	0.271	0.0125	0.3525	0.5025	0.1325
		C_{22}	0.086	0.4575	0.0475	0.4575	0.0375
		C_{23}	0.186	0.0525	0.4725	0.4125	0.0625
		C_{24}	0.321	0.2375	0.0775	0.5475	0.1375
		C_{25}	0.136	0.5075	0.1775	0.3075	0.0075
M_3	0.32	C_{31}	0.2667	0.5075	0.0275	0.3975	0.0675
		C_{32}	0.4767	0.5	0.16	0.34	0
		C_{33}	0.2567	0.42	0.1	0.4	0.08
M_4	0.02	C_{41}	0.5533	0.4425	0.0525	0.4625	0.0425
		C_{42}	0.2333	0.405	0.155	0.405	0.035
		C_{43}	0.2133	0.4825	0.1125	0.2425	0.1625
Priority				0.323	0.17	0.395	0.112
Ranking				2	3	1	4

Table 5 Result of D-AHP method when the information is with medium credibility

Main criteria		Sub-criteria		Alternatives			
M_i		C_{ij}		X_1	X_2	X_3	X_4
M_1	0.2325	C_{11}	0.2369	0.3081	0.2456	0.2631	0.1831
		C_{12}	0.3144	0.2769	0.1894	0.2294	0.3044
		C_{13}	0.2519	0.3025	0.2275	0.29	0.18
		C_{14}	0.1969	0.3094	0.2069	0.2819	0.2019
M_2	0.3075	$C21$	0.2284	0.1906	0.2756	0.3131	0.2206
		C_{22}	0.1544	0.3019	0.1994	0.3019	0.1969
		C_{23}	0.1944	0.2006	0.3056	0.2906	0.2031
		C_{24}	0.2484	0.2469	0.2069	0.3244	0.2219
		C_{25}	0.1744	0.3144	0.2319	0.2644	0.1894
M_3	0.2675	C_{31}	0.3111	0.3144	0.1944	0.2869	0.2044
		C_{32}	0.3811	0.3125	0.2275	0.2725	0.1875
		C_{33}	0.3078	0.2925	0.2125	0.2875	0.2075
M_4	0.1925	C_{41}	0.4067	0.2981	0.2006	0.3031	0.1981
		C_{42}	0.3	0.2888	0.2262	0.2888	0.1962
		C_{43}	0.2933	0.3081	0.2156	0.2481	0.2281
Priority				0.284	0.223	0.284	0.209
Ranking				1	3	1	4

consistent, although these situations have different discriminative capability in the differences of alternatives' weights. When the information is considered to be lowly credible, which means that experts do not clearly distinguish the alternatives, so the differences among derived weights of alternatives are small. With the increase in information's credibility (λ becomes lower), the slight differences among alternatives' weights can be distinguished due to the improvement of experts' cognitive capability. As a result, the priority weights of suppliers present relatively obvious difference, as shown in the situation of high credibility. Thus, the impact of information's credibility in the D-AHP method on the results of ranking alternatives has been illustrated clearly.

Table 6 Result of D-AHP method when the information is with low credibility

Main criteria		Sub-criteria		Alternatives			
M_i		C_{ij}		X_1	X_2	X_3	X_4
M_1	0.2412	C_{11}	0.2434	0.2791	0.2478	0.2566	0.2166
		C_{12}	0.2822	0.2634	0.2197	0.2397	0.2772
		C_{13}	0.2509	0.2762	0.2388	0.27	0.215
		C_{14}	0.2234	0.2797	0.2284	0.2659	0.2259
M_2	0.2788	C_{21}	0.2114	0.2203	0.2628	0.2816	0.2353
		C_{22}	0.1818	0.2759	0.2247	0.2759	0.2234
		C_{23}	0.1978	0.2253	0.2778	0.2703	0.2266
		C_{24}	0.2194	0.2484	0.2284	0.2872	0.2359
		C_{25}	0.1898	0.2822	0.2409	0.2572	0.2197
M_3	0.2588	C_{31}	0.3185	0.2822	0.2222	0.2684	0.2272
		C_{32}	0.3652	0.2812	0.2388	0.2612	0.2188
		C_{33}	0.3163	0.2712	0.2312	0.2688	0.2288
M_4	0.2212	C_{41}	0.3822	0.2741	0.2253	0.2766	0.2241
		C_{42}	0.3111	0.2694	0.2381	0.2694	0.2231
		C_{43}	0.3067	0.2791	0.2328	0.2491	0.2391
Priority				0.268	0.236	0.266	0.229
Ranking				1	3	2	4

5 Conclusions

In this paper, the MCDM problem has been studied by using our previous proposed D-AHP method, where the credibility of providing information is numerically analyzed. Regarding the value of parameter λ that associates with the cognitive ability of experts, it takes a smaller value if the comparison information is provided by an authoritative expert which means the information is with higher credibility, while it takes a higher value if the comparison information comes from an expert whose judgment is with low belief that implies the information is with lower credibility. The results show that the credibility of information slightly impacts the ranking of alternatives, and the priority weights of alternatives have been influenced in a relatively obvious degree. In the future research, the criteria for measuring the credibility of information will be studied.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

References

Antoine V, Quost B, Masson MH, Denoeux T (2014) CEVCLUS: evidential clustering with instance-level constraints for relational data. Soft Comput 18(7):1321–1335

Aplak HS, Sogut MZ (2013) Game theory approach in decisional process of energy management for industrial sector. Energy Convers Manag 74:70–80

Aplak HS, Türkbey O (2013) Fuzzy logic based game theory applications in multi-criteria decision making process. J Intell Fuzzy Syst 25(2):359–371

Chen YH, Chao RJ (2012) Supplier selection using consistent fuzzy preference relations. Expert Syst Appl 39(3):3233–3240

Chen SJJ, Hwang CL, Beckmann MJ, Krelle W (1992) Fuzzy multiple attribute decision making: methods and applications. Springer, New York

Dempster AP (1967) Upper and lower probabilities induced by a multivalued mapping. Ann Math Stat 38(2):325–339

Deng Y (2012) D numbers: theory and applications. J Inf Comput Sci 9(9):2421–2428

Deng X, Jiang W (2018) An evidential axiomatic design approach for decision making using the evaluation of belief structure satisfaction to uncertain target values. Int J Intell Syst 33(1):15–32

Deng X, Hu Y, Deng Y, Mahadevan S (2014a) Environmental impact assessment based on D numbers. Expert Syst Appl 41(2):635–643

Deng X, Hu Y, Deng Y, Mahadevan S (2014b) Supplier selection using AHP methodology extended by D numbers. Expert Syst Appl 41(1):156–167

Deng X, Han D, Dezert J, Deng Y, Shyr Y (2016) Evidence combination from an evolutionary game theory perspective. IEEE Trans Cybern 46(9):2070–2082

Deng X, Xiao F, Deng Y (2017) An improved distance-based total uncertainty measure in belief function theory. Appl Intell 46(4):898–915

Denoeux T (2013) Maximum likelihood estimation from uncertain data in the belief function framework. IEEE Trans Knowl Data Eng 25(1):119–130

Fei L, Wang H, Chen L, Deng Y (2017) A new vector valued similarity measure for intuitionistic fuzzy sets based on OWA operators. Iran J Fuzzy Syst 15(5):31–49

García-Cascales MS, Lamata MT (2012) On rank reversal and TOPSIS method. Math Comput Model 56(5):123–132

Herrera-Viedma E, Herrera F, Chiclana F, Luque M (2004) Some issues on consistency of fuzzy preference relations. Eur J Oper Res 154(1):98–109

Herrera-Viedma E, Alonso S, Chiclana F, Herrera F (2007) A consensus model for group decision making with incomplete fuzzy preference relations. IEEE Trans Fuzzy Syst 15(5):863–877

Jiang W, Wang S (2017) An uncertainty measure for interval-valued evidences. Int J Comput Commun Control 12(5):631–644

Jiang W, Zhan J (2017) A modified combination rule in generalized evidence theory. Appl Intell 46(3):630–640

Jiang W, Wei B, Tang Y, Zhou D (2017a) Ordered visibility graph average aggregation operator: an application in produced water management. Chaos Interdiscip J Nonlinear Sci 27(2):023117

Jiang W, Xie C, Zhuang M, Tang Y (2017b) Failure mode and effects analysis based on a novel fuzzy evidential method. Appl Soft Comput 57:672–683

Jiang W, Wei B, Liu X, Li X, Zheng H (2018) Intuitionistic fuzzy power aggregation operator based on entropy and its application in decision making. Int J Intell Syst 33(1):49–67

Kang B, Chhipi-Shrestha G, Deng Y, Hewage K, Sadiq R (2017) Stable strategies analysis based on the utility of Z-number in the evolutionary games. Appl Math Comput. https://doi.org/10.1016/j.amc.2017.12.006

Liu HC, You JX, Fan XJ, Lin QL (2014) Failure mode and effects analysis using D numbers and grey relational projection method. Expert Syst Appl 41(10):4670–4679

Liu T, Deng Y, Chan F (2017) Evidential supplier selection based on DEMATEL and game theory. Int J Fuzzy Syst. https://doi.org/10.1007/s40,815-017-0400-4

Liu, B., Hu, Y., Deng, Y.: New failure mode and effects analysis based on D numbers downscaling method. Int J Comput Commun Control **13**(2) (2018, in press)

Nie S, Hu B, Li Y, Hu Z, Huang GH (2011) Identification of filter management strategy in fluid power systems under uncertainty: an interval-fuzzy parameter integer nonlinear programming method. Int J Syst Sci 42(3):429–448

Opricovic S, Tzeng GH (2004) Compromise solution by MCDM methods: a comparative analysis of VIKOR and TOPSIS. Eur J Oper Res 156(2):445–455

Opricovic S, Tzeng GH (2007) Extended VIKOR method in comparison with outranking methods. Eur J Oper Res 178(2):514–529

Peldschus F, Zavadskas EK (2005) Fuzzy matrix games multi-criteria model for decision-making in engineering. Informatica 16(1):107–120

Ribeiro RA (1996) Fuzzy multiple attribute decision making: a review and new preference elicitation techniques. Fuzzy Sets Syst 78(2):155–181

Saaty TL (1980) The analytic hierarchy process: planning, priority setting, resources allocation. McGraw-Hill, Inc., New York

Sayadi MK, Heydari M, Shahanaghi K (2009) Extension of VIKOR method for decision making problem with interval numbers. Appl Math Model 33(5):2257–2262

Shafer G (1976) A mathematical theory of evidence. Princeton University Press, Princeton

Tanino T (1984) Fuzzy preference orderings in group decision making. Fuzzy Sets Syst 12(12):117–131

Tsaur RC (2011) Decision risk analysis for an interval TOPSIS method. Appl Math Comput 218(8):4295–4304

Wang Z, Bauch CT, Bhattacharyya S, d'Onofrio A, Manfredi P, Perc M, Perra N, Salathé M, Zhao D (2016) Statistical physics of vaccination. Phys Rep 664:1–113

Wang Z, Jusup M, Wang RW, Shi L, Iwasa Y, Moreno Y, Kurths J (2017) Onymity promotes cooperation in social dilemma experiments. Sci Adv 3(3):e1601444

Wei GW (2008) Maximizing deviation method for multiple attribute decision making in intuitionistic fuzzy setting. Knowl Based Syst 21(8):833–836

Xu Z (2007) A survey of preference relations. Int J Gen Syst 36(2):179–203

Xu H, Deng Y (2018) Dependent evidence combination based on Shearman coefficient and Pearson coefficient. IEEE Access. https://doi.org/10.1109/ACCESS.2017.2783320

Xu Z, Yager RR (2008) Dynamic intuitionistic fuzzy multi-attribute decision making. Int J Approx Reason 48(1):246–262

Xu S, Jiang W, Deng X, Shou Y (2018) A modified Physarum-inspired model for the user equilibrium traffic assignment problem. Appl Math Model 55:340–353

Yager RR (1992) Decision making under Dempster–Shafer uncertainties. Int J Gen Syst 20(3):233–245

Yager RR (2014) An intuitionistic view of the Dempster–Shafer belief structure. Soft Comput 18(11):2091–2099

Yager RR, Liu L et al (2008) Classic works of the Dempster–Shafer theory of belief functions, vol 219. Springer, Berlin

Yang JB, Xu DL (2013) Evidential reasoning rule for evidence combination. Artif Intell 205:1–29

Yang M, Khan FI, Sadiq R, Amyotte P (2013) A rough set-based game theoretical approach for environmental decision-making: a case of offshore oil and gas operations. Process Saf Environ Prot 91(3):172–182

Zhang R, Ashuri B, Deng Y (2017) A novel method for forecasting time series based on fuzzy logic and visibility graph. Adv Data Anal Classif 11(4):759–783

Zhang Q, Li M, Deng Y (2018) Measure the structure similarity of nodes in complex networks based on relative entropy. Phys A Stat Mech Its Appl 491:749–763

Zheng H, Deng Y (2018a) Evaluation method based on fuzzy relations between Dempster-Shafer belief structure. Int J Intell Syst. https://doi.org/10.1002/int.21956

Zheng X, Deng Y (2018b) Dependence assessment in human reliability analysis based on evidence credibility decay model and IOWA operator. Ann Nucl Energy 112:673–684

Zheng H, Deng Y, Hu Y (2017) Fuzzy evidential influence diagram and its evaluation algorithm. Knowl Based Syst 131:28–45