

Study on Evidence Reliability Weighting Method Based on Two-tuple Linguistic

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Abstract: For evidence reliability weighting under incomplete information, a method is proposed based on two-tuple linguistic. Experts describe the evidence with the indexes which are familiar with, and then assess the evidence based on these indexes and give linguistic assessment information. Subsequently, two-tuple linguistic based on incomplete linguistic information is employed to combine the assessment information from experts and conclude the reliability of the evidence. This method allows the linguistic description of assessment information given by experts, so as to better avoid some problems, such as, information distortion and loss, etc. This method is applicable when incomplete information exists, and able to well solve the practical problem that experts fail to conduct complete assessment due to their limited professional knowledge. This paper illustrates the feasibility and effectiveness of this method with an example.

Keywords: *evidence reliability; two-tuple linguistic; linguistic assessment information; incomplete linguistic information; multi-objective programming*

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I. INTRODUCTION

In the group decision-making with incomplete information, evidence theory has been widely applied as it can well explain some important cognitive concepts, e.g. “uncertain” and “unknown”, and combine the professions of experts to provide highly accurate assessment information for decision-making. When evidence theory is applied in group decision-making, the

results of decision-making depend on the reliability of every evidence as the combination rules of evidence theory are given. According to the existing references, there are three types of methods for evidence reliability weighting. 1. Evidence reliability is obtained by training BP neural networks [1], which needs to train tremendous data. 2. Evidence reliability weighting is conducted based on typical samples, and reliability depends on the Hamming distance between the typical values of evidence and target mode, which is not applicable to the uniform and continuous distribution of evidence reliability [2]. 3. Reliability weight is obtained using the membership function in fuzzy mathematics, which depends much on practical application and has very complicated calculation of reliability [3]. Besides these shortcomings, these methods have one common problem that they are not applicable when incomplete information exists. This paper proposes to apply two-tuple linguistic in the process of evidence reliability weighting. The information needed by experts in the process of evidence reliability weighting, e.g. knowledge and experience, etc. is described with the indexes they are familiar with, and experts are only required to give linguistic assessment information on these indexes. Then, the assessment information given by experts is combined to obtain the weight of evidence reliability assigned by each expert. Meanwhile, two-tuple linguistic cannot obtain the weight of index directly when incomplete linguistic information exists, so this paper establishes the index optimization model with the goal of

minimizing total deviation, so as to solve this problem. In the process of evidence reliability weighting, experts give the assessment information of each index mostly in linguistic form, so two-tuple linguistic can effectively prevent such problems as information distortion and loss, etc. in the aggregation and calculation of linguistic assessment information, so as to realize better accuracy and reliability of calculation. Meanwhile, the calculation method of index weight in two-tuple linguistic is improved to make two-tuple linguistic more suitable for the condition when both assessment information and weight information of indexes are incomplete.

II. EVIDENCE RELIABILITY WEIGHTING

METHOD BASED ON TWO-TUPLE LINGUISTIC

A. Overview of Two-tuple Linguistic Theory

Two-tuple linguistic representation model is an information processing method put forth by Herrera, a professor in Spain. It employs two tuples (s_k, a_k) to represent linguistic assessment information for relevant operations. As a linguistic information processing method, the two-tuple linguistic proposed by Professor Herrera solves the problem that numerical scale cannot reflect the assessment information of decision-makers accurately and effectively. Compared with other linguistic information processing methods, it can effectively prevent such problems as information distortion and loss, etc. in the aggregation and calculation of linguistic assessment information, so it has better accuracy and reliability of calculation.

The linguistic assessment results of the object given by experts are represented by two tuples (s_k, a_k) . The element s_k represents that the linguistic assessment information given by expert is the k th element in the predefined linguistic term set $S = \{s_0, s_1, \dots, s_T\}$. For instance, there

is a linguistic term set composed of 7 assessment linguistic terms.

$$S = \{s_0 = \text{Very Poor (VP)}, s_1 = \text{Poor (P)},$$

$$s_2 = \text{Medium Poor (MP)}, s_3 = \text{Fair (F)},$$

$$s_4 = \text{Medium Good (MG)}, s_5 = \text{Good (G)},$$

$$s_6 = \text{Good (G)}\}$$

Definition 1 [1] If $s_k \in S$ is a linguistic term, the two tuples can be obtained using the following function θ :

$$\theta : S \rightarrow S \times [-0.5, 0.5] \quad (1)$$

$$\theta(s_k) = (s_k, 0), s_k \in S \quad (2)$$

Definition 2 [1] If $S = \{s_0, s_1, \dots, s_T\}$ is a linguistic term set composed of $T + 1$ linguistic terms, and the real number $\beta \in [0, T]$ is obtained using the symbol aggregation method from the linguistic term set S , β can be explained in two-tuple linguistic information with the following function Δ :

$$\Delta : [0, T] \rightarrow S \times [-0.5, 0.5] \quad (4)$$

$$\Delta(\beta) = \begin{cases} s_k, k = \text{round}(\beta) \\ a_k = \beta - k, a_k \in [-0.5, 0.5] \end{cases} \quad (5)$$

In which, round is the rounding calculator.

Definition 3 [1] If (s_k, a_k) is a two-tuple, there will be an inverse function Δ^{-1} , which is converted into the real number $\beta \in [0, T]$:

$$\Delta^{-1} : S \times [-0.5, 0.5] \rightarrow [0, T] \quad (6)$$

$$\Delta^{-1}(s_k, a_k) = k + a_k = \beta \quad (7)$$

If the expert $E_v \in E (v = 1, 2, \dots, t)$ assesses the decision-making object $A_i \in A (i = 1, 2, \dots, n)$ with regard to the index $G_j \in G (j = 1, 2, \dots, m)$, the assessment value given by expert E_v to the object A_i with regard to the index G_j is $s_{ij}^v \in S$, so there is the linguistic assessment matrix $S^v = [s_{ij}^v]_{m \times n}$.

$$\Phi_i^v[(s_{1i}^v, 0), (s_{2i}^v, 0), \dots, (s_{mi}^v, 0)] = \Delta \left[\sum_{j=1}^m \Delta^{-1}(s_{ji}^v, 0) w_j \right] = \Delta \left[\sum_{j=1}^m \beta_j w_j \right] \quad (8)$$

The comprehensive assessment value obtained by combining the assessment information given by experts is converted into evidence reliability. If the reliability of the evidence provided by expert E_v for the decision-making on A_i is m_i^v , there is:

$$\sum_{i=1}^n m_i^v = 1 \quad (9)$$

To satisfy Equation (9), the result of Equation (8) is normalized, so there is:

$$m_i^v = \Phi_i^v / \sum_{i=1}^n \Phi_i^v \quad (10)$$

B. Two-tuple Linguistic with Incomplete Linguistic Information

Two-tuple linguistic requires experts to give judgments or make decisions on all indexes in the assessment index system. Due to the complexity and uncertainty of a problem, experts can only assess the indexes in the fields they are familiar with, so linguistic assessment information is

Definition 4 [5] If, in the two-tuple $(s_{ij}^v, 0)$,

$s_{ij}^v \in S$ is the value given by expert E_v to the object A_i with regard to the index G_j and $W_1 = (w_1, w_2, \dots, w_m)$ is the index weight assigned by expert panel, which will be further detailed hereinafter, the comprehensive assessment value Φ_i^v given by expert to A_i based on own profession is calculated as follows:

incomplete, and the weight information given by experts to indexes is incomplete. Two-tuple linguistic is improved to be applicable to the group decision-making with incomplete information. Reliable decision can be made by utilizing two-tuple linguistic for the high fidelity of experts' assessment information and employing evidence theory for combination of experts' assessment information.

1) Incompleteness of Linguistic Assessment Information

References [2-4] studied the group decision-making with incomplete linguistic information. In References [2,3], the incomplete judgment information could not be given by experts for some reasons, but they had some internal connections mathematically, so incomplete elements must be calculated. Thus, it was not applicable when assessment information could not be given by experts due to their limited knowledge and their internal connections could not be identified. Reference [4] converted the incomplete additive linguistic judgment matrix given by experts into the incomplete

complementary judgment matrix, and employed the line normalization to calculate the sequence vector of the incomplete complementary judgment matrix, but it only considered the incompleteness of assessment value. The two-tuple linguistic proposed in this paper based on incomplete linguistic information is applicable when the assessment value of index is incomplete linguistic and the weight of index is incomplete information. The incompleteness of index weight is caused as experts cannot give the weight information to the indexes they are not familiar with.

Let incomplete linguistic assessment information be $s_{ij}^v = 0$ in the linguistic assessment matrix, which means that experts cannot assess the object A_i with regard to the index G_j correctly, so they do not give corresponding assessment information. The assessment matrix is as follows:

$$E_v = \begin{matrix} & A_1 & A_2 & \cdots & A_i & \cdots & A_n \\ \begin{matrix} G_1 \\ G_2 \\ \vdots \\ G_j \\ \vdots \end{matrix} & \begin{vmatrix} VG & MG & \cdots & MG & \cdots & MG \\ G & G & \cdots & MG & \cdots & F \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \\ 0 & 0 & 0 & 0 & 0 & 0 \\ \cdots & \cdots & \cdots & \cdots & \cdots & \cdots \end{vmatrix} \end{matrix}$$

When an expert is not familiar with an index, he cannot assess the index of the object correctly. Thus, when there is any zero element in assessment matrix, all the elements in the same line are zero. Zero elements are added to incomplete linguistic assessment matrix, so as to obtain the complete matrix. Evidence reliability represents the degree of an expert's support for an evidence. Two-tuple linguistic is employed for evidence reliability weighting. In other words, each complete linguistic assessment matrix is utilized to determine the degree of the expert's support for each object.

2) Calculation of Index Weights

When linguistic assessment information is incomplete, the two-tuple linguistic method cannot well determine index weights, so it is necessary to recalculate the index weights. The determination of index weights means to determine the relationship among indexes with regard to their importance. Index weights can be determined by employing three methods, namely, subjective weighting method, objective weighting method and subjective-objective weighting method (also known as combination weighting method). Subjective weighting method is the first and mature method for weighting, and determines the weight of each index based on experts' subjective attention to the index. The original data in this method are obtained based on the subjective judgments of experts. The common subjective weighting method includes analytic hierarchy process (AHP) and expert survey method (Delphi) [6]. Objective weighting method depends on the relationship among original data for determining their weights, and its results of decision-making or assessment have very strong mathematic and theoretical basis. The common objective weighting method includes entropy technology [7], deviation method [8] and objective programming [9, 10]. Combination weighting method includes linear weighted combination method and multiplication combination method [11]. Reference [5] utilized the distance formula of two-tuple linguistic to calculate the deviation of an expert's judgment about an index from the other experts' judgments about the index. When the total deviation of expert panel's judgment about the index was larger, there was larger difference between the comments given by expert panel on the index, and the weight granted to the index should be lower. Subjective weighting method is significantly affected by subjective factors. In the meanwhile, experts can only assign weights to the indexes they are familiar with when incomplete information exists, and are unable to

assign accurate weights to other indexes in the index system. Entropy technology is utilized to reflect the degree of variation of indexes, and believes that the indexes with higher degree of variation can provide more information, they may assign higher weights to such indexes. Deviation method assigns the weights based on the capability of indexes to distinguish a scheme. When the deviation of an index in the scheme is larger, it is believed that the index can have more impacts on the rank of the scheme, so higher weight should be assigned to the index. All these methods are not applicable when there is incomplete information. The method of establishing multi-objective optimization model with the goal of minimizing total deviation can be used for index weighting with incomplete information, which has been verified in Reference [9].

If t experts judge the importance of indexes through pair-wise comparison, t judgment matrixes $G^k = (g_{ij}^k)_{m \times m}, k = 1, 2, \dots, t$ are obtained. g_{ij}^k stands for the k th expert's judgment about the importance of the i th index G_i relative to the j th index G_j . The 1-9 scale method proposed by Saaty is employed for grading to satisfy $g_{ij}^k g_{ji}^k = 1, \forall i, j \in \{1, 2, \dots, m\}$. If the expert E_v cannot judge the importance of the index i relative to the index j , it is recorded in the judgment matrix G^k . $g_{ij}^k = \varepsilon$ describes the incomplete information in judgment matrix and defines an incomplete parameter matrix $\Delta^k = (\delta_{ij}^k)_{m \times m}$, in which:

$$\delta_{ij}^k = \begin{cases} 1, & g_{ij}^k \neq \varepsilon \\ 0, & g_{ij}^k = \varepsilon \end{cases}, (k = 1, 2, \dots, t) \quad (11)$$

Under ideal conditions, there is:

$$g_{ij}^k = w_i / w_j \Leftrightarrow w_i = g_{ij}^k w_j,$$

$$i, j = 1, 2, \dots, m; k = 1, 2, \dots, t \quad (12)$$

When experts have different judgments about the index weight, there is $w_{1i} \neq g_{ij}^k w_{1j}$,

$i, j = 1, 2, \dots, m; k = 1, 2, \dots, t$. The deviation variable γ_{ij}^k is defined as follows:

$$\gamma_{ij}^k = \delta_{ij}^k |w_i - g_{ij}^k w_j| \quad (13)$$

The total deviation of t judgment matrixes is:

$$F_{ij}(w_1) = \varphi_{ij} \sum_{k=1}^t |\gamma_{ij}^k| = \varphi_{ij} \sum_{k=1}^t \delta_{ij}^k |w_i - g_{ij}^k w_j|, \quad i, j = 1, 2, \dots, m \quad (14)$$

In which, φ_{ij} is the coefficient of normalization, $\varphi_{ij} = (\sum_{k=1}^t \delta_{ij}^k)^{-1}$.

Obviously, the lower value of $F_{ij}(w_1)$, the more similar judgments of all experts. Equation (10) is better satisfied. Thus, the objective programming model is established as follows:

$$\min F_{ij}(w_1) = \varphi_{ij} \sum_{k=1}^t \delta_{ij}^k |w_i - g_{ij}^k w_j|, \quad i, j = 1, 2, \dots, m; i \neq j \quad (15)$$

$$s.t. \sum_{i=1}^m w_i = 1, w_i \geq 0, i = 1, 2, \dots, m \quad (16)$$

The solution of the above objective programming model can be converted into the

solution of the following objective programming models:

$$\min J = \sum_{i=1}^m \sum_{j=1, j \neq i}^m (d_{ij}^+ + d_{ij}^-) \quad (17)$$

$$s.t. \varphi_{ij} \sum_{k=1}^t \delta_{ij}^k |w_i - g_{ij}^k w_j| + d_{ij}^+ + d_{ij}^- = 0, \quad (18)$$

$$i, j = 1, 2, \dots, m; i \neq j, \quad (18)$$

$$\sum_{i=1}^m w_i = 1, w_i \geq 0, i = 1, 2, \dots, m \quad (19)$$

$$d_{ij}^+ \geq 0, d_{ij}^- \geq 0, d_{ij}^+ d_{ij}^- = 0, \quad (20)$$

$$i, j = 1, 2, \dots, m; i \neq j$$

In which, d_{ij}^+, d_{ij}^- stand for positive/negative deviation variable respectively.

By optimizing and solving models (17)~(20), the index weight $W_1 = (w_1, w_2, \dots, w_m)$ can be obtained.

III. Calculation Procedure of Evidence Reliability Based on Two-tuple Linguistic

Assuming that expert $E_v \in E (v = 1, 2, \dots, t)$ assesses the decision-making object $A_i \in A (i = 1, 2, \dots, n)$ with regard to the index $G_j \in G (j = 1, 2, \dots, m)$, expert E_v gives the assessment value $s_{ij}^v \in S$ to the object A_i with regard to the index G_j and expert panel assigns the index weight $W_1 = (w_1, w_2, \dots, w_m)$. The specific calculation procedure of evidence reliability is as follows:

a) Experts describe the evidence brought forward in the analysis with the indexes they are familiar with according to their professions, in order to keep the information in the evidence maximally. To standardize the contents of indexes and limit the scope of indexes, expert panel may establish an assessment index system based on their knowledge and experience prior to decision-making. Then, the object is assessed based on the indexes experts are familiar with, and the assessment information is given in the form of linguistic information. Based on the predefined orderly natural linguistic term set, the linguistic assessment information of all experts is converted into the initial incomplete linguistic decision-making matrix. Equation (2) is utilized to convert the initial incomplete linguistic decision-making matrix into the two-tuple form, and the incomplete element is 0.

b) Experts employ the 1-9 scale method proposed by Saaty in the pair-wise comparison to determine the mutual importance of relevant indexes in the professional fields. g_{ij}^k represents the k th expert's judgment about the importance of the i th index G_i relative to the j th index G_j . Any index they are not familiar with is not compared, and its weight is $g_{ij}^k = \varepsilon$. Thus, the judgment matrix of the k th expert is G_k . A multi-objective optimization model is established with the goal of minimizing the total deviation variable of experts' judgment matrixes, and then solved to obtain the index weight $W_1 = (w_1, w_2, \dots, w_m)$.

c) Equations (8) and (10) are utilized to combine the assessment information in each matrix, and the result is the reliability of the evidence provided by the expert.

IV. CASE ANALYSIS

A venture capital company should make an optimum investment decision on a fund, so it invites 4 experts (represented by E_1 , E_2 , E_3 and E_4) to analyze the decision of investment in four target companies (represented by A_1 , A_2 , A_3 and A_4) with regard to five indexes, namely, enterprise resources (G_1), direct economic benefits (G_2), project collaborative effect (G_3), strategic contribution rate (G_4) and investment risks (G_5).

a) If the linguistic term set S consists of 7 assessment linguistic terms, and the assessment information is given by experts in the form of natural language, the initial term matrixes given by experts are as follows:

$$\begin{aligned}
 E_1 = & \begin{matrix} & A_1 & A_2 & A_3 & A_4 \\ G_1 & VG & MG & MG & MG \\ G_2 & G & G & MG & F \\ G_3 & G & MP & P & P \\ G_4 & 0 & 0 & 0 & 0 \\ G_5 & 0 & 0 & 0 & 0 \end{matrix} \\
 E_2 = & \begin{matrix} & A_1 & A_2 & A_3 & A_4 \\ G_1 & VG & G & MG & G \\ G_2 & G & G & F & G \\ G_3 & 0 & 0 & 0 & 0 \\ G_4 & 0 & 0 & 0 & 0 \\ G_5 & MG & G & G & MG \end{matrix} \\
 E_3 = & \begin{matrix} & A_1 & A_2 & A_3 & A_4 \\ G_1 & VG & G & MG & G \\ G_2 & G & G & F & G \\ G_3 & 0 & 0 & 0 & 0 \\ G_4 & G & MG & G & MG \\ G_5 & G & G & G & MG \end{matrix} \\
 E_4 = & \begin{matrix} & A_1 & A_2 & A_3 & A_4 \\ G_1 & VG & G & G & G \\ G_2 & 0 & 0 & 0 & 0 \\ G_3 & G & F & MG & P \\ G_4 & MG & MG & G & G \\ G_5 & MG & G & G & MG \end{matrix}
 \end{aligned}$$

Based on Equation (2), the initial linguistic matrixes given by four experts are converted into the two-tuple form as follows:

$$\begin{aligned}
 E_1 = & \begin{matrix} (s_6,0)(s_4,0)(s_4,0)(s_4,0) \\ (s_5,0)(s_5,0)(s_4,0)(s_3,0) \\ (s_5,0)(s_2,0)(s_1,0)(s_1,0) \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{matrix}, & E_2 = & \begin{matrix} (s_6,0)(s_5,0)(s_4,0)(s_5,0) \\ (s_5,0)(s_5,0)(s_3,0)(s_5,0) \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ (s_4,0)(s_5,0)(s_5,0)(s_4,0) \end{matrix} \\
 E_3 = & \begin{matrix} (s_6,0)(s_5,0)(s_4,0)(s_5,0) \\ (s_5,0)(s_5,0)(s_3,0)(s_5,0) \\ 0 & 0 & 0 & 0 \\ (s_5,0)(s_4,0)(s_5,0)(s_4,0) \\ (s_5,0)(s_5,0)(s_5,0)(s_4,0) \end{matrix}, & E_4 = & \begin{matrix} (s_6,0)(s_5,0)(s_5,0)(s_5,0) \\ 0 & 0 & 0 & 0 \\ (s_5,0)(s_3,0)(s_4,0)(s_1,0) \\ (s_4,0)(s_4,0)(s_5,0)(s_5,0) \\ (s_4,0)(s_5,0)(s_5,0)(s_4,0) \end{matrix}
 \end{aligned}$$

b) Experts employ the 1-9 scale method to compare the importance of the indexes they are familiar with, and the judgment matrixes given by four experts are as follows:

$$\begin{aligned}
 E_1 = & \begin{matrix} 1 & 4 & 3 & \varepsilon & \varepsilon \\ 1/4 & 1 & 1/3 & \varepsilon & \varepsilon \\ 1/3 & 3 & 1 & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & 1 & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & \varepsilon & 1 \end{matrix}, & E_2 = & \begin{matrix} 1 & 4 & \varepsilon & \varepsilon & 1/4 \\ 1/4 & 1 & \varepsilon & \varepsilon & 1/4 \\ \varepsilon & \varepsilon & 1 & \varepsilon & \varepsilon \\ \varepsilon & \varepsilon & \varepsilon & 1 & \varepsilon \\ 4 & 4 & \varepsilon & \varepsilon & 1 \end{matrix}, \\
 E_3 = & \begin{matrix} 1 & 3 & \varepsilon & 2 & 1/4 \\ 1/3 & 1 & \varepsilon & 1/3 & 1/4 \\ \varepsilon & \varepsilon & 1 & \varepsilon & \varepsilon \\ 1/2 & 3 & \varepsilon & 1 & 3 \\ 4 & 4 & \varepsilon & 1/3 & 1 \end{matrix}, & E_4 = & \begin{matrix} 1 & \varepsilon & 3 & 2 & 1/3 \\ \varepsilon & 1 & \varepsilon & \varepsilon & \varepsilon \\ 1/3 & \varepsilon & 1 & 1/2 & 1/3 \\ 1/2 & \varepsilon & 2 & 1 & 3 \\ 3 & \varepsilon & 3 & 1/3 & 1 \end{matrix}
 \end{aligned}$$

The models (17)~(20) are utilized to establish the multi-objective programming models for index weights. The optimization function `fmincon` provided by MATLAB is employed to solve these models, so there is:

$$J = 1.4309, w_1 = 0.3040, w_2 = 0.0829, w_3 = 0.1013, w_4 = 0.2260, w_5 = 0.2857,$$

$$d_{12}^- = 0, d_{12}^+ = 0, d_{13}^- = 0, d_{13}^+ = 0,$$

$$d_{14}^- = 0.1480, d_{14}^+ = 0, d_{15}^- = 0,$$

$$d_{15}^+ = 0.2247, d_{21}^- = 0.0015, d_{21}^+ = 0,$$

$$d_{23}^- = 0, d_{23}^+ = 0.0491, d_{24}^- = 0,$$

$$d_{24}^+ = 0.0076, d_{25}^- = 0, d_{25}^+ = 0.0115$$

$$d_{31}^- = 0, d_{31}^+ = 0, d_{32}^- = 0.1474, d_{32}^+ = 0,$$

$$\begin{aligned}
d_{34}^- &= 0.0117, d_{34}^+ = 0, d_{35}^- = 0, \\
d_{35}^+ &= 0.0061, d_{41}^- = 0, d_{41}^+ = 0.0740, \\
d_{42}^- &= 0.0228, d_{42}^+ = 0.0228, d_{42}^- = 0, \\
d_{43}^- &= 0, d_{43}^+ = 0.0233, d_{45}^- = 0.6311, \\
d_{45}^+ &= 0, d_{51}^- = 0.4146, d_{51}^+ = 0.4146, \\
d_{52}^- &= 0.0460, d_{52}^+ = 0, d_{53}^- = 0.0183, \\
d_{53}^+ &= 0, d_{54}^- = 0, d_{54}^+ = 0.2104.
\end{aligned}$$

c) Equations (8) and (10) are employed to combine the assessment information given by each expert, so as to obtain the reliability of evidence given by each expert during the analysis of each object. The results are shown in Table 1.

TABLE 1 RELIABILITY OF EVIDENCE

Decision-making Scheme	A ₁	A ₂	A ₃	A ₄
E ₁	0.352	0.235	0.212	0.201
E ₂	0.266	0.264	0.228	0.242
E ₃	0.281	0.250	0.236	0.233
E ₄	0.259	0.246	0.265	0.230

V. CONCLUSION

As evidence reliability is directly given by experts based on their own knowledge, experience and preference, etc., it is highly subjective and may easily result in the conflict in the combination of evidences that are equally important. Therefore, this paper proposes an evidence reliability weighting method based on two-tuple linguistics. In this method, the information used in the expert analysis is described with the indexes experts are familiar with, so experts are only required to analyze the indexes they are familiar with in their professional fields. After that, the two-tuple linguistic method is utilized to combine the

incomplete linguistic assessment information given by experts, so as to obtain the reliability of evidence given by each expert in the analysis of each decision-making scheme. This method converts the process of experts' evidence reliability weighting into the process of experts' decision-making according to multiple rules, so as to effectively lower the fuzziness and inaccuracy of weighting. Meanwhile, the index weights are taken into account in the combination of information by employing two-tuple linguistic, so the evidence obtained from the combination of information has a weight. Therefore, this method can be effective to solve the conflict among evidences.

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