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Performance Evaluation Model of Logistics Enterprises Considering Mass Data in the Internet of Things

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Abstract

In allusion to such problems as the no use of the structural information of the dataset in the traditional clustering effectiveness evaluation function and the excessive noisy point deletion, the research method integrating theoretical analysis and empirical analysis is adopted to establish KPI management index system model for telecommunication enterprises. A new clustering effectiveness evaluation function is proposed in this article. Specifically, PCA (principal component analysis) method in multivariate statistics is applied in the performance evaluation systems of telecommunication enterprises, and meanwhile relevant instances are analyzed and evaluated. Therein, the evaluation index system has the features of simpleness, strong practicability, low operation cost and high accuracy, and the geometric structure features of dataset are added for the performance evaluation of telecommunication enterprises. Additionally, distance critical value L is added in the compact indexes and the constraint condition thereof is also given in order to construct a new clustering effectiveness evaluation index model which can more scientifically and rationally reflect the actual evaluation result.

Keywords:*Clustering analysis; Effectiveness evaluation function; Fuzzy soft set; Internet of things; Big data; Comprehensive evaluation; Information integration*

1. Introduction

The distributed intelligent control based on multi-system (MAS) is not only the future of industrial control, but also another leap during the control science development, wherein the inter-system cooperation is the key control point. In MAS, when one resource finitely encounters the tasks unable to be finished thereby, this resource has to interact and cooperate with other resources in the system so as to form a team to jointly undertake the task, and such team is called as coalition [1-2]. As a frontier topic of the control theory, coalition issue is always widely concerned by the scholars at home and abroad, and meanwhile rich research achievements have been obtained in the aspects of coalition generation [3-4], coalition formation [5-6], utility allocation [7-8], *etc*. However, in some complex control and decision-making systems, advantages and disadvantages of coalition utility are directly related to the task completion condition and can be used to judge whether the coalition formed thereby can efficiently and smoothly finish the corresponding tasks. In other words, it is necessary to track and evaluate the working condition of the present coalition in a real-time manner in order to reflect the decision effect and guide the subsequent task execution [9]. Coalition effectiveness is closely related to such factors as member ability, coordination performance, communication cost and member familiarity, and these factors can be only expressed by some fuzzy, summary and uncertain natural linguistic terms

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rather than quantitative numerical values, thus bringing certain difficulty to evaluation [10].

For the evaluation mechanism, the most common evaluation methods include simple weighting method and fuzzy comprehensive evaluation method [11]. These methods usually require the evaluation experts to consider the same evaluation index set in order to give the evaluation information of individuals. In actual evaluation problems, the evaluation experts are usually from different fields, namely different organizations or departments, and each expert has different knowledge and experiences, so each evaluation expert may only concern her/his interesting and familiar indexes in the evaluation index set. If the evaluation experts are required to evaluate all indexes in the evaluation index set, then they will easily get significantly different evaluation results and accordingly cause false judgment, and this is unfavorable for the final decision of the decision-maker. Actually, the fuzzy soft set theory can well handle the above problems.

In allusion to the above problems, an effective coalition evaluation method considering the different individual evaluation index sets of different experts is designed in this article, and meanwhile the fuzzy soft set theory is adopted for the comprehensive evaluation of the coalition. The key point of this method is to adopt the fuzzy soft set theory to handle the individual evaluation index sets of different experts and integrate the evaluation results of different experts on this basis in order to obtain the comprehensive evaluation result of the coalition. The organization structure of the article is as follows: this article firstly describes the coalition evaluation problem, then introduces the fuzzy soft set theory based coalition evaluation process and finally gives experiment results and analysis conclusions.

2. Big Data Clustering Effectiveness Evaluation Function

During the effectiveness analysis under noisy environment, in the consideration of the clustering compactness and separability, the noise points shall be included in order to make the effectiveness index sensitive to noise and outliers. MPO clustering effectiveness evaluation function is composed of compactness measurement and separability measurement, wherein the compactness measurement is jointly determined by fuzzy membership matrix and cluster number c and denotes the compactness in the cluster; the separability measurement is defined as the distance among different fuzzy sets and denotes the separation degree of different clusters. On the basis of considering the monotone tendency of PC index along with the increment of cluster number c and improving PX index, u_M and $\left(\frac{c+1}{c-1}\right)^{1/2}$ $(2 \le c \le n)$ are introduced therein as the adjustment index to reduce the influence of the cluster number change on the result, thus to obtain compactness measurement $Com(U,c)$:

$$Com(U,c) = \left(\frac{c+1}{c-1}\right)^{1/2} \sum_{i=1}^{c} \sum_{j=1}^{n} u_{ij}^2 / u_M \tag{1}$$

In the above formula, u_{ij} denotes the membership of the j th element belonging to the i th cluster , $u_M = \min_{1 \le i \le c} \sum_{j=1}^{n} u_{ij}^2$, and $\sum_{j=1}^{n} u_{ij}^2 / u_M$ is used to measure the compactness of cluster i relatively to the most compact cluster. $Com(U,c)$ denotes the compactness of the data in the cluster, and the larger value thereof indicates the better fuzzy division obtained thereby.

In order to obtain correct division in the clustering environment with noise points and outliers, the separability measurement is defined as follows:

$$Sep(U,c)=\frac{1}{n}\sum_{j=1}^{n}\left(\sum_{a=1}^{c-1}\sum_{b=a+1}^{c}O_{abj}(U;c)\right) \tag{2}$$

In the above formula, $O_{abj}(U;c)=\begin{cases}1-\left|u_{aj}-u_{bj}\right|, if \left|u_{aj}-u_{bj}\right|\geq T, a\neq b\\ 0, other.\end{cases}$, u_{aj} and u_{bj} respectively denote the membership values of the *j*th element to cluster a and b.

In $O_{abj}(U;c)$, threshold value T is applied to eliminate the fuzzy data points in the cluster border [14], and these data points are the noise points.

$Sep(U,c)$ is used to calculate the sum of the separation degrees of all data points in the data set obtained thereby through the membership matrix. The smaller $Sep(U,c)$ value indicates the clearer cluster division.

MPO function is the difference between the compactness measurement and the separability measurement:

$$MPO(U,V)=Com(U,c)-Scp(U,c) \tag{3}$$

According to the comparison with multiple clustering effectiveness indexes including PC, FS, XB, OS, PACES, CO and W, MPO can well determine the cluster number and can avoid the influence of noise points on data set. However, the structural information of the data set is not used in MPO function, so MPO function is not sensitive to distance. In this article, the geometric structure features of the data set are added on the basis of MPO function in order to avoid the influence of single theory on the detection result. In the separability measurement, the noise points shall be carefully deleted, because excessive deletion will cause data loss. Accordingly, a new critical value L is added in $sep(c)$ to restrain the noise point scope jointly with the original critical value T in order to avoid result inaccuracy caused by data loss.

3. Construction of New Clustering Effectiveness Evaluation Function

3.1. Compactness Measurement

In allusion to the problems that MPO function is not directly contacted with the geometric structure of the data set and the clustering effect cannot be comprehensively evaluated, the geometric structure information reflecting the internal compactness in the cluster is integrated in the compactness measurement $Com(U,c)$ in order to obtain new compactness index $Com'(U,c,d)$.

$$Com'(U,c,d)=\sum_{i=1}^{c}\frac{\sum_{j=1}^{n}u_{ij}^{2}}{u_M\, d_M}\left(\frac{c+1}{c-1}\right)^{1/2} \tag{4}$$

In the above formula, d_M is Euclidean distance, and the improved function not only includes the distance from x_j object to the cluster center v_i, but also includes the membership function value of x_j to cluster i. $Com'(U,c,d)$ value can reflect the compactness of the data points in the cluster, and the larger value indicates the greater compactness of the elements in the cluster and the better division effect.

3.2. Separability Measurement Based on Dual Constraints to Noise Points

During the clustering process, noise points and isolated points can significantly influence the clustering result. According to literature [13], the critical value T of the membership is adopted in MPO function to preliminarily separate the noise points under probability condition, but the independent application of probability constraint for defining noise point scope may cause data loss. Therefore, in order to more accurately determine the noise points, the critical value L of the geometric structure is added in this article on the basis of the critical value T of the membership in order to adopt two critical values to jointly determine the noise points and accordingly effectively avoid the data loss under the condition of single theory. The separability measurement combining the probability condition and the geometric structure is defined as follows:

$$Sep'(U,c,d) = \frac{1}{n\sum_{j=1}^{n}\sqrt[3]{\frac{1}{c}\sum_{i=1}^{c} d_{ij}}}\sum_{j=1}^{n}\left\{\sum_{a=1}^{c-1}\sum_{b=a+1}^{c} W(U;c)\right\} \tag{5}$$

In the above formula,

$$W(U,c,d) = \begin{cases} 0, \left|u_{aj}-u_{bj}\right| \le T \quad and \quad \left|d_{aj}-d_{bj}\right| \le L_j \quad while \quad a \ne b. \\ 1-\left|u_{aj}-u_{bj}\right|, other \end{cases} \tag{6}$$

Two critical values T and L are set to eliminate the fuzzy and uncertain points in the cluster border. According to different clustering data distribution structures, values T and L can be given by the experts or customized according to the function. In this article, according to massive data experiments, the two critical values are preliminarily given as follows: $T = 0.01$ and $L_j = \sqrt[3]{\frac{1}{c}\sum_{i=1}^{c} d_{ij}}$, wherein d_{ij} denotes the distance from the j th element to the i th cluster. $W(U;c,d)$ is the separation degree of the given data point. The smaller $sep'(c)$ value indicates the clearer cluster division effect.

3.3. Construction of Clustering Effectiveness Function

The compactness measurement and the separability measurement are integrated to obtain the following new clustering effectiveness evaluation function:

$$VS(U,V) = \frac{Com'(U,c,d)}{Sep'(U,c,d)} \tag{7}$$

A good cluster is required to have large $Com'(U,c,d)$ and small $Sep'(U,c,d)$, and $VS(U,V)$ is used to define the effectiveness function, wherein the larger $VS(U,V)$ value indicates the better clustering division effect.

4. Coalition Evaluation Method Based on Fuzzy Soft Set

4.1. Coalition Evaluation Process

As shown in Figure 1 when solving the coalition evaluation problem, firstly, the user shall provide the coalition $R = \{r_1, r_2, \cdots, r_q\}$ to be evaluated and the evaluation index set $D = \{d_1, d_2, \cdots, d_n\}$; then, each expert shall give the individual evaluation index set $D_k = \{d_1^k, d_2^k, \cdots, d_{l_k}^k\}$ and the evaluation matrix $V_k = (v_{ti}^k)_{q \times l_k}$; then, the fuzzy soft set shall be used to integrate the evaluation values obtained from all evaluation experts in order to obtain the final evaluation result.

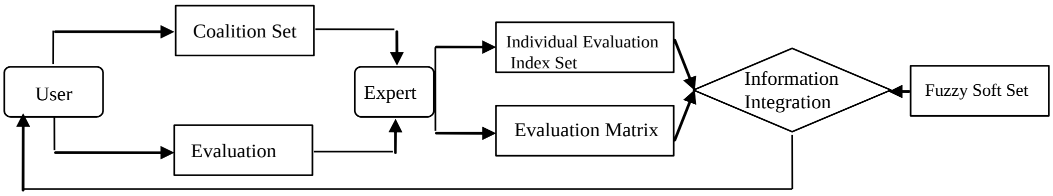

Figure 1. Coalition Evaluation Process Based on Fuzzy Soft Set

4.1.1. Conversion of Evaluation Matrix and Fuzzy Soft Set: According to the individual evaluation set D_k and the evaluation matrix V_k of each evaluation expert p_k, the evaluation information of the evaluation coalition regarding each evaluation index is expressed as the fuzzy soft set (F_k, D_k), as shown in formula (8)

$$
\begin{aligned}
(F_k, D_k) = \{ & d_1^k = \{r_1/v_{11}^k, r_2/v_{21}^k, \cdots, r_q/v_{q1}^k\}, \\
& d_2^k = \{r_1/v_{12}^k, r_2/v_{22}^k, \cdots, r_q/v_{q2}^k\}, \\
& \vdots \qquad\qquad \vdots \\
& d_{l_k}^k = \{r_1/v_{1l_k}^k, r_2/v_{2l_k}^k, \cdots, r_q/v_{ql_k}^k\} \\
\} &
\end{aligned} \tag{8}
$$

4.1.2. Information Integration: The comprehensive evaluation matrix can be obtained only after the evaluation information of each expert is integrated. The integration method is as follows: implement "AND" operation orderly for the fuzzy soft set $(F_1 D_1)$, (F_2, D_2), …, (F_m, D_m). The operation result is expressed by (G, E) as follows:

$$(G,E) = (G, D_1 \times D_2 \times \cdots \times D_n) = (F_1, D_1) \wedge (F_2, D_2) \wedge \cdots \wedge (F_m, D_m) \tag{9}$$

Meanwhile, for $\forall(\hat{d}_1, \hat{d}_2, \cdots, \hat{d}_n) \in D_1 \times D_2 \times \cdots \times D_m$, the following formula can be obtained:

$$G(\hat{d}_1, \hat{d}_2, \cdots, \hat{d}_m) = F_1(d_1^{'}) \cap F_2(d_2^{'}) \cap \cdots \cap F_m(d_m^{'}) \tag{10}$$

Obviously, (G,E) is also a fuzzy soft set. According to definition 2, the parameters of (G,E) are obtained from the combination of the evaluation index sets $D_1, D_2, \cdots, D_m$ of n experts. If (G,E) includes L parameters and $E = \{e_1, e_2, \cdots, e_L\}$ is true, then (G,E) can be expressed as follows:

$$
\begin{aligned}
(G,E) = \{ & e_1 = \left\{ r_1 / \mu_{11}, r_2 / \mu_{21}, \cdots, r_q / \mu_{q1} \right\}, \\
& e_2 = \left\{ r_1 / \mu_{12}, r_2 / \mu_{22}, \cdots, r_q / \mu_{q2} \right\}, \\
& \quad \vdots \qquad\qquad \vdots \\
& e_L = \left\{ r_1 / \mu_{1L}, r_2 / \mu_{2L}, \cdots, r_q / \mu_{qL} \right\} \\
& \}
\end{aligned}
\tag{11}
$$

In the above formula, μ_{tj} denotes the coincidence degree between the evaluated coalition r_t and the state described by the combined parameter e_j ($j = 1, 2, \cdots, L$). Two conditions shall be considered for μ_{tj} :

(1) If $D_1 \cap D_2 \cap \cdots \cap D_m = \varnothing$ is true, namely: the individual evaluation indexes of the evaluation experts are completely different from each other, then $L = l_1 \cdot l_2 \cdot \cdots \cdot l_m$ is true and any e_j can be expressed as $e_j = (\hat{d}_1^j, \hat{d}_2^j, \cdots, \hat{d}_m^j)$, namely: parameter e_j is obtained from the combination of parameter $\hat{d}_1^j$ in D_1 , parameter $\hat{d}_2^j$ in D_2 , …, parameter $\hat{d}_m^j$ in D_m , and μ_{tj} is determined by formula (12).

$$
\mu_{tj} = \min_{\substack{\hat{d}_x^j \in \left\{ \hat{d}_1^j, \hat{d}_2^j, \cdots, \hat{d}_m^j \right\} \\ k \in \{1, 2, \cdots, m\}}} \left\{ v_{tx}^k \right\}
\tag{12}
$$

According to formula (8), if the coordination evaluation made by an expert for a certain coalition is 0.7 and the innovation ability evaluation made by another expert for the same coalition is 0.9, then the evaluation result obtained after information integration for this coalition is also 0.7, namely: the evaluation value for “good coordination and innovation ability” is 0.7.

(2) If $D_1 \cap D_2 \cap \cdots \cap D_m \neq \varnothing$ is true, namely: the individual evaluation indexes of some experts are the same, then $L < l_1 \cdot l_2 \cdot \cdots \cdot l_m$ is true and $e_j = (\hat{d}_1^j, \hat{d}_2^j, \cdots, \hat{d}_{\hat{m}}^j)$ ($\hat{m} < m$), namely: parameter e_j is respectively obtained from the combination of $\hat{m}$ different parameters in $D_1, D_2, \cdots, D_m$. If the common evaluation index d_c ($d_c \in D$) exists in $D_{k_1}, D_{k_2}, \cdots, D_{k_m}$, then μ_{tj} is determined by formula (13).

$$
\mu_{tj} = \min \left\{ \min_{\substack{\hat{d}_x^j \in \left\{ \hat{d}_1^j, \hat{d}_2^j, \cdots, \hat{d}_{\hat{m}}^j \right\} \\ k \in \{1, 2, \cdots, \hat{m}\}}} \left\{ v_{tx}^k \right\}, \lambda_t \right\}
\tag{13}
$$

$$
\lambda_t = \operatorname*{average}_{k \in \{k_1, k_2, \cdots, k_m\}} \left\{ v_{tc}^k \right\}
\tag{14}
$$

In other words, when the individual index sets of the evaluation experts have intersection, formula (13) is firstly used to obtain the average value of the same index evaluation values and then formula (14) is used to obtain the average value of the composite index e_j .

At present, most researches regarding the fuzzy soft set are only focused on condition (1), namely: the parameter sets are required to be different from each other (without any intersection), but such assumption may be not consistent with the actual situation. However, the method proposed in this article takes the parameter set intersection into consideration.

The evaluation score $Score(r_t)$ of each coalition to be evaluated is calculated according to CT .

$$Score(r_x) = s_x - t_x \tag{15}$$

$$s_x = \sum_{y=1}^{q} ct_{xy} \tag{16}$$

$$t_y = \sum_{x=1}^{q} ct_{xy} \tag{17}$$

In formulae (15) and (16), s_x denotes the sum of the x th row in CT and means that the evaluation value of r_x is more than the number sum of the evaluation parameters of other members in R , and t_y denotes the sum of the y th column in CT and means that the evaluation value of r_y is more than the number sum of the evaluation parameters of other members in R . Therefore, $Score(r_t)$ denotes the superiority of r_t in R , namely: the larger r_t value indicates the superior r_t .

Coalition has numerous influencing factors and it is difficult to quantitatively describe these factors by quantitative method, and the significance of using this method to evaluate the coalition lies in the fact that this method can reflect the different preferences of the evaluation experts and the uncertainty of the evaluation information in order to enable the evaluation experts to flexibly express their subjective judgments. Meanwhile, the evaluation information of multiple evaluators can be integrated through "AND" operation of the fuzzy soft set, thus to obtain comprehensive evaluation result.

5. Instance Analysis

$R = \{r_1, r_2, r_3, r_4\}$ denotes the coalition to be evaluated, $D = \{d_1, d_2, d_3, d_4, d_5, d_6\}$ denotes the six attributes of each coalition, namely the evaluation indexes, and $P = \{p_1, p_2, p_3\}$ denotes three evaluation experts.

(1) Each experts give the individual evaluation index sets $D_1 = \{d_1, d_2, d_5\}$, $D_2 = \{d_1, d_3, d_4\}$ and $D_3 = \{d_1, d_5, d_6\}$ according to the known knowledge and experience and meanwhile give the corresponding evaluation matrixes V_1 , V_2 and V_3 .

$$V_1 = \begin{matrix} & d_1 & d_2 & d_5 \\ r_1 & 0.9 & 0.6 & 0.8 \\ r_2 & 0.8 & 0.7 & 0.6 \\ r_3 & 0.9 & 0.5 & 0.4 \\ r_4 & 0.7 & 0.8 & 0.5 \end{matrix} \quad V_2 = \begin{matrix} & d_1 & d_3 & d_4 \\ r_1 & 0.8 & 0.9 & 0.6 \\ r_2 & 0.9 & 0.8 & 0.5 \\ r_3 & 0.7 & 0.5 & 0.4 \\ r_4 & 0.7 & 0.6 & 0.8 \end{matrix} \quad V_3 = \begin{matrix} & d_1 & d_5 & d_6 \\ r_1 & 0.6 & 0.8 & 0.9 \\ r_2 & 0.7 & 0.6 & 1 \\ r_3 & 0.6 & 0.7 & 0.4 \\ r_4 & 0.8 & 0.4 & 0.6 \end{matrix}$$

(2) V_1 , V_2 and V_3 are respectively expressed as the fuzzy soft sets (F_1, D_1) , (F_2, D_2) and (F_3, D_3) .

$$
\begin{aligned}
(F_1, D_1) = \{ d_1 &= \{ r_1/0.9, r_2/0.8, r_3/0.9, r_4/0.7 \}, \\
d_2 &= \{ r_1/0.6, r_2/0.7, r_3/0.5, r_4/0.8 \}, \\
d_5 &= \{ r_1/0.8, r_2/0.6, r_3/0.4, r_4/0.5 \} \\
\}
\end{aligned}
$$

$$
\begin{aligned}
(F_2, D_2) = \{ d_1 &= \{ r_1/0.8, r_2/0.9, r_3/0.7, r_4/0.7 \}, \\
d_3 &= \{ r_1/0.9, r_2/0.8, r_3/0.5, r_4/0.6 \}, \\
d_4 &= \{ r_1/0.6, r_2/0.5, r_3/0.4, r_4/0.8 \} \\
\}
\end{aligned}
$$

$$
\begin{aligned}
(F_3, D_3) = \{ d_1 &= \{ r_1/0.6, r_2/0.7, r_3/0.6, r_4/0.8 \}, \\
d_5 &= \{ r_1/0.8, r_2/0.6, r_3/0.7, r_4/0.4 \}, \\
d_6 &= \{ r_1/0.9, r_2/1, r_3/0.4, r_4/0.6 \} \\
\}
\end{aligned}
$$

(3) The fuzzy soft sets are adopted for the information integration for V_1 , V_2 and V_3 , namely: implement "AND" operation for (F_1, D_1) , (F_2, D_2) and (F_3, D_3) to obtain $(G, E) = (G, D_1 \times D_2 \times D_3) = (F_1, D_1) \wedge (F_2, D_2) \wedge (F_3, D_3)$. Since $D_1 \cap D_2 \cap D_3 \neq \varnothing$ is true, the number of the parameters in parameter set E is $L < 3 \times 3 \times 3 = 27$.

Firstly, we assume that $\hat{E} = \{\hat{e}_1, \hat{e}_2, \cdots, \hat{e}_{27}\}$ is obtained from the three parameters respectively provided by D_1 , D_2 and D_3 , as shown in Table 1.

Table 1. Parameter Composition of $\hat{E} = \{\hat{e}_1, \hat{e}_2, \cdots, \hat{e}_{27}\}$

$\hat{e}_j$	$\hat{e}_1$	$\hat{e}_2$	$\hat{e}_3$	$\hat{e}_4$	$\hat{e}_5$	$\hat{e}_6$	$\hat{e}_7$	$\hat{e}_8$	$\hat{e}_9$
Original Parameters	d_1	$d_1 d_5$	$d_1 d_6$	$d_1 d_3$	$d_1 d_3 d_5$	$d_1 d_3 d_6$	$d_1 d_4$	$d_1 d_4 d_5$	$d_1 d_4 d_6$
$\hat{e}_j$	$\hat{e}_{10}$	$\hat{e}_{11}$	$\hat{e}_{12}$	$\hat{e}_{13}$	$\hat{e}_{14}$	$\hat{e}_{15}$	$\hat{e}_{16}$	$\hat{e}_{17}$	$\hat{e}_{18}$
Original Parameters	$d_1 d_2$	$d_1 d_2 d_5$	$d_1 d_2 d_6$	$d_1 d_2 d_3$	$d_2 d_3 d_5$	$d_2 d_3 d_6$	$d_1 d_2 d_4$	$d_2 d_4 d_5$	$d_2 d_4 d_6$
$\hat{e}_j$	$\hat{e}_{19}$	$\hat{e}_{20}$	$\hat{e}_{21}$	$\hat{e}_{22}$	$\hat{e}_{23}$	$\hat{e}_{24}$	$\hat{e}_{25}$	$\hat{e}_{26}$	$\hat{e}_{27}$
Original Parameters	$d_1 d_5$	$d_1 d_5$	$d_1 d_5 d_6$	$d_1 d_3 d_5$	$d_3 d_5$	$d_3 d_5 d_6$	$d_1 d_4 d_5$	$d_4 d_5$	$d_4 d_5 d_6$

According to Table 2, $\hat{e}_2 = \hat{e}_{19} = \hat{e}_{20} = \{d_1 d_5\}$, $\hat{e}_5 = \hat{e}_{22} = \{d_1 d_3 d_5\}$ and $\hat{e}_8 = \hat{e}_{25} = \{d_1 d_4 d_5\}$, so the number of the parameters in E is $L = 23$. If E is set as $E = \{e_1, e_2, \cdots, e_{23}\}$, then the parameters of E are as shown in Table 2.

Table 2. Parameter Composition of $E = \{e_1, e_2, \cdots, e_{23}\}$

e_j	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8
Original Parameters	d_1	$d_1 d_5$	$d_1 d_6$	$d_1 d_3$	$d_1 d_3 d_5$	$d_1 d_3 d_6$	$d_1 d_4$	$d_1 d_4 d_5$

e_j	e_9	e_{10}	e_{11}	e_{12}	e_{13}	e_{14}	e_{15}	e_{16}
Original Parameters	$d_1d_4d_6$	d_1d_2	$d_1d_2d_5$	$d_1d_2d_6$	$d_1d_2d_3$	$d_2d_3d_5$	$d_2d_3d_6$	$d_1d_2d_4$
e_j	e_{17}	e_{18}	e_{19}	e_{20}	e_{21}	e_{22}	e_{23}	
Original Parameters	$d_2d_4d_5$	$d_2d_4d_6$	$d_1d_5d_6$	d_3d_5	$d_3d_5d_6$	d_4d_5	$d_4d_5d_6$	

The fuzzy soft set (G,E) is calculated according to formulae (8) and (9). We will take μ_{16} and μ_{13} to explain the calculation process of (G,E).

$$\mu_{16} = \min\left\{v_{11}^1, v_{13}^2, v_{16}^3\right\} = \{0.9, 0.9, 0.9\} = 0.9$$

$$\mu_{13} = \min\left\{\frac{v_{11}^1 + v_{11}^2}{2}, v_{16}^3\right\} = \min\left\{\frac{0.9+0.8}{2}, 0.9\right\} = 0.85$$

(G,E) can be obtained through an analogy way, and the tabular form thereof is as shown in Table 3.

Table 3. Tabular Form of Fuzzy Soft Set (G,E)

μ_{tj}	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8	e_9	e_{10}	e_{11}	e_{12}
r_1	0.77	0.8	0.85	0.75	0.8	0.9	0.6	0.6	0.6	0.6	0.6	0.6
r_2	0.8	0.6	0.85	0.75	0.6	0.8	0.5	0.5	0.5	0.7	0.6	0.7
r_3	0.73	0.55	0.4	0.75	0.5	0.4	0.4	0.4	0.4	0.5	0.5	0.4
r_4	0.73	0.4	0.6	0.6	0.4	0.6	0.75	0.4	0.6	0.75	0.4	0.6
μ_{tj}	e_{13}	e_{14}	e_{15}	e_{16}	e_{17}	e_{18}	e_{19}	e_{20}	e_{21}	e_{22}	e_{23}	
r_1	0.6	0.6	0.6	0.6	0.6	0.6	0.8	0.8	0.8	0.6	0.6	
r_2	0.7	0.6	0.7	0.5	0.5	0.5	0.6	0.6	0.6	0.5	0.5	
r_3	0.5	0.5	0.4	0.4	0.4	0.4	0.4	0.5	0.4	0.4	0.4	
r_4	0.6	0.4	0.6	0.8	0.4	0.6	0.5	0.45	0.5	0.45	0.5	

(4) The comparison table $CT = (ct_{xy})_{4\times4}$ is calculated according to formulae (11) and (12), as shown in Table 4.

Table 4. Comparison Table

ct_{xy}	r_1	r_2	r_3	r_4
r_1	23	18	23	20
r_2	9	23	23	18
r_3	1	1	23	8
r_4	8	6	17	23

(5) The evaluation score $Score(r_t)$ is calculated according to formulae (13) and (14), as shown in Table 5.

Table 5. Evaluation Score

	s_x	t_x	$Score(r_t)$
r_1	84	41	43
r_2	73	48	25
r_3	33	86	-53
r_4	54	69	-15

According to Table 6, $Score(r_1) > Score(r_2) > Score(r_3) > Score(r_4)$, so coalition r_1 is the best, and is orderly followed by r_2, r_3 and r_4.

According to the above instance, the method proposed in this article takes different individual evaluation index sets of the experts and the allowable intersection of individual evaluation index sets into consideration. The evaluations made by the experts for the coalitions are expressed by uncertain information so that the experts can flexibly express their individual subjective judgment, and the fuzzy soft set is introduced therein for the information integration of the evaluation results of the experts in order to obtain the comprehensive evaluation result.

6. Conclusion

In this article, the fuzzy soft set is introduced for comprehensively evaluating the coalitions. During the evaluation process, it is considered that the experts have different individual evaluation index sets and the individual evaluation index sets of the experts are allowed to be overlapped. Meanwhile, the fuzzy soft set is introduced therein to integrate the evaluation information of the experts in order to obtain the comprehensive evaluation result. In conclusion, this method can not only make comprehensive use of expert knowledge and experience, but also reflect the information uncertainty and incompleteness during the evaluation process, wherein such evaluation process is consistent with human thinking & judgment process and has the features of flexibility, effectiveness and rationality.

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