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Group Decision-Making Method for Dynamic Cloud Model Based on Cumulative Prospect Theory

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Abstract

Group decision-making is a situation faced when individuals collectively make a choice from the alternatives before them. Aiming to the drawback that not all plans can be evaluated by a single expert during group decision-making process, a group decision-making method for dynamic cloud distribution is proposed in this paper based on cumulative prospect theory. First, experts and plans were divided into groups according to the classification rule, and plans were described with the cloud model. The expectation, the entropy and the super entropy decision matrix were structured respectively. Then, the maximum and minimum values in decision matrix were set as positive and negative reference points. The parameter values of cumulative cloud prospect were calculated and the synthesis prospect values of every group were obtained. Finally, the plans were sorted based on the mean of synthesis prospect values for every group, and illustrated by specific examples. The ranking results show that the proposed method is rationality and practicability. So the proposed method can be widely used in group decision-making of grouping scheme or grouping expert.

Keywords*: Dynamic group decision-making; Cumulative prospect theory; Cloud model; Comprehensive prospect value*

1. Introduction

As modern science and technology develops rapidly, people start to pay more and more attention to group decision-making methods, which have important applicable values and developmental prospects in many fields such as investment decision-making, intelligent transportation and network planning, *etc.*, [1-2]. Group decision-making methods mainly contain multiple attribute decision making(MADM) and multiple objective decision making(MODM), in which the former primarily makes a decision about the known solution and the latter produces a scheme about unknown solution [3-5]. Before using these two kinds of group decision-making methods, experts must evaluate all solutions. But actually with the increase number of solutions and experts, it is impossible for all experts to evaluate every solution. Furthermore, considering the effect of external factors and conditions, the value of each factor which was used to group decision-making is uncertain. Therefore, as experts and solutions are divided into different groups, this has important practical value to research how the plans are ordered in the group whose value factors are uncertain.

At present, there are many researches focusing on group decision-making methods. For instance, delphi method researches some ways to solve the problems of group decision-making by several rounds of discussion [6]; Jian Huang *et. al.*, put forward a novel model of group decision-making with the help of FDAHP[7]; Xiaopeng Zhang *et. al.*, researched the performance problems about dynamic group decision-making by means of the view of

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dynamics [8]. Despite the benefits of these researches, most of them were based on the conditions that all experts had already know the evaluations of all solutions. And in the practical process of decision-making, experts, who are effected by some factors such as personal experiences, attitudes to the problem and personal habits, may have subjective preference or disgust for different solutions, and this can effects final decision-making results. Therefore, it is necessary to take the preference of decision makers into account in group decision-making.

For this purpose, to solve the problem that part of the evaluations are unknown and property values are given in the form of cloud model, this paper proposes a novel method of group decision-making based on Cumulative Prospect Theory. The rationality and practicability of proposed method has been illustrated by specific examples.

2. Basic Knowledge

2.1. Cumulative Prospect Theory

Cumulative Prospect Theory is an uncertain decision-making theory that based on the hypothesis of bounded rationality, and it was proposed by Kahneman and Tversky in the view of prospect theory. This method can adapt to human's thinking modes in contrast with expected utility theory which is fully rational [9]. Cumulative Prospect Theory mainly considers gains and losses of problems. In other words, people usually use "risk reversion" measurement when facing profits. But when facing losses, people usually use some "risk seeking" measurement. The prospect value V is mainly decided by value function v and the accumulated weight function π. As it is followed:

$$V(f)=V(f^{+})+V(f^{-})=\sum_{i=0}^{n}v(x_i)\pi_i^{+}+\sum_{i=0}^{n}v(x_i)\pi_i^{-} \quad (1)$$

Where i is profit value and when $i \geq 0$, i represents profits, so $\pi_i=\pi_i^{+}$; When $i<0$, i represents losses, so $\pi_i=\pi_i^{-}$.

The value function can effectively describe the feature that decision makers prefer to avoid risks while facing profits and seek risks while facing losses, which is followed:

$$v(x)=\begin{cases} x^{\alpha} & x \geq 0 \\ -\lambda(-x)^{\beta} & x<0 \end{cases} \quad (2)$$

Where x is the difference between solutions and reference point. When $x \geq 0$, it presents profits; when $x<0$,it represents losses. $\alpha \in [0,1]$ is the risk preference coefficient. $\beta \in [0,1]$ is the risk aversion coefficient. When $\alpha=\beta=1$, both of them are risk neutral. λ is the avoiding loss coefficient. when $\lambda>1$, decision makers will be more sensitive to losses.

2.2. Cloud Model

At 1995, Deyi Li proposed the cloud model, which realizes the conversion from qualitative to quantitative of uncertainty information [10-11]. It is expressed as follows:

Definition 1(Cloud Model [10]): A random realization of a qualitative concept of C in domain U is $x \in U$. If the certainty of to C is $\mu(x) \in [0,1]$, then the distribution of x in domain U is in cloud form, in which $\mu(x)$ is a random number with certain stability. And the distribution is expressed as $C(X)$. x is named as cloud droplet.

There are 4 basic properties for cloud model as follows:

(i)For any cloud droplet x in domain U , the mapping of x to interval [0-1] is essentially a one-to-many transformation;

(ii) $\mu(x)$ is a random number with a certain probability distribution;

(iii) x is out of order. The more cloud droplets, the better the expression of the overall characteristics of qualitative concept;

(vi)Both the probability that x appear and its contributions for concepts are proportional to certainty.

Cloud model describes the uncertainty of C by using expectation, entropy and hyper entropy, where the expectation is the most typical sample value; entropy is uncertainty; hyper entropy is the aggregation level of cloud droplet x.

3. Methodology

3.1. The Description of Problems about Group Decision-Making

If there are m groups of cloud model, and the k th plan group is $O_k = \{o_{1k}, o_{2k}, \cdots, o_{lk}\}$ .where $1 \le k \le m$ .The attribute set of group k is $A_k = \{a_{1k}, a_{2k}, \cdots, a_{qk}\}$,in which each element is independent; $w_k = \{w_{1k}, w_{2k}, \cdots, w_{qk}\}$ is weight vector and it meets $0 \le w_{jk} \le 1$and $\sum_{j=1}^{q} w_{jk} = 1$.Decision-makers need to evaluate each attribute in every solution and describe attributes with cloud membership. So the attribute value vector in solution t is represented as follows:

$$\mu(A_t) = \{\mu(a_{1t}), \mu(a_{2t}), \cdots, \mu(a_{qt})\}$$
(3)

Where $1 \le t \le l$.

3.2. The Steps of Dynamic Group Decision-Making

According to the problems described in 3.1, the specific steps of group decision-making method for dynamic cloud model based on cumulative prospect theory are represented as follows:

(i)According to the actual condition, attributes A_{ik} and weight values w_{ik} of each solution in the k th group in cloud model form are provided, where $0 \le w_{ik} \le 1$, $i \in [1, q]$, $k \in [1, m]$. Then attributes are normalized through the method in reference [12], average value E_k, entropy En_k and hyper entropy Hc_k are calculated and weighted cloud decision matrix $[E_k]$, $[En_k]$ and $[Hc_k]$ are obtained;

(ii)The maximum and minimum values in weighed cloud decision matrix represent positive and negative reference points respectively, as follows:

$$\begin{cases} R_k^{+} = \max[R_k] \\ R_k^{-} = \min[R_k] \end{cases} \tag{4}$$

Where R represents average E , entropy En and hyper entropy Hc respectively.

Then the distance between positive and negative reference points is calculated:

$$\begin{cases} D(R_k^{+}) = \sqrt{\sum_{i=1}^{q} [(R_{ik} - R_k^{+}) \cdot w_i]^2} \\ D(R_k^{-}) = \sqrt{\sum_{i=1}^{q} [(R_{ik} - R_k^{-}) \cdot w_i]^2} \end{cases} \tag{5}$$

(iii) Cumulative cloud prospect values of each parameter in the k th group are calculated according to Formula (1) and (2). As follows:

$$V_{R_k}(x) = [D(R_k^{+}(x_i))]^{\alpha} \cdot \pi_i^{+} - \lambda[-D(R_k^{-}(x_i))]^{\beta} \cdot \pi_i^{-} \tag{6}$$

$$\begin{cases} \pi_i^+ = \dfrac{D(R_k^+)}{D(R_k^+)+D(R_k^-)} \\ \pi_i^- = \dfrac{D(R_k^-)}{D(R_k^+)+D(R_k^-)} \end{cases} \tag{7}$$

Therefore, the results obtained from reference [13] are used that $\alpha=\beta=0.88$ and $\lambda=2.25$, comprehensive prospect values of each solution are obtained:

$$V_k = \sqrt[3]{V_{E_k}(x)\times V_{En_k}(x)\times V_{Hc_k}(x)} \tag{8}$$

(iv) m groups are sorted according to the mean values of comprehensive prospect value, and recorded as $L=\{L_1,L_2,\cdots,L_m\}$.In the meantime , solutions in the k th group are sorted according to comprehensive prospect value, and they are recorded as $O_k'=\{o_{1k}',o_{2k}',\cdots,o_{lk}'\}$. Finally, a solution with the biggest comprehensive prospect value in solution group L_1 is selected and is regarded as the best solution;

(v) The solution with second biggest comprehensive prospect value is selected from solution group L_1, and it is contrasted with the best solution in L_2. If former is greater than latter, the former is regarded as the second best solution. Otherwise, the solution that has the biggest comprehensive prospect value in L_2 is set as the second best solution;

(vi) If the former solution in step (iv) works out, then compare the solution that has the third biggest comprehensive prospect value to the solution from L_1 that has the biggest comprehensive prospect value from L_2.If the former solution is greater than the latter one, the former will be the third best solution; If the latter solution in step (iv) works out, we will mutually compare the second biggest comprehensive prospect value in L_1 and L_2 to the biggest comprehensive prospect value in L_3, and then the biggest one is the third best solution; By parity of reasoning, it comes to an end until all solutions are compared.

4. Result Analysis and Discussion

For instance, in an investment engineering project, a company plans to develop 9 new services to enlarging business which are $X_1, X_2, X_3, X_4, X_5, X_6, X_7, X_8, X_9$. And they invite 3 investment companies to do a risk assessment to 3 new services before investing. Suppose that three investment companies evaluate them according to 4 attribute indicators, including return time A_1, risk possibility A_2, investment strength A_3 and income A_4. A_1, A_2 and A_3 are cost type attribute indexes; A_4 is profits attribute index. Weight coefficients of attribute indexes are shown in Table 1.

Table 1. Weight Coefficient of Attribute Indexes

attribute indexes	A_1	A_2	A_3	A_4
weight	0.20	0.25	0.25	0.3

For convenient calculation, supposing that when three investment companies S_1, S_2 and S_3 assess new services, they will give attribute values in form of Triangular cloud distribution, as shown in Table 2.

Table 2. Triangular Cloud Distribution of Nine New Businesses from Three Investment Companies

attribute / new business		A_1	A_2	A_3	A_4
S_1	X_1	[0.35,0.40,0.43]	[0.42,0.48,0.50]	[0.27,0.34,0.40]	[0.85,0.90,0.93]
	X_2	[0.28,0.34,0.38]	[0.30,0.35,0.38]	[0.30,0.34,0.36]	[0.90,0.95,0.97]
	X_3	[0.32,0.40,0.45]	[0.45,0.48,0.50]	[0.25,0.30,0.35]	[0.89,0.93,0.96]
S_2	X_4	[0.30,0.38,0.43]	[0.45,0.50,0.55]	[0.14,0.18,0.20]	[0.91,0.93,0.95]
	X_5	[0.18,0.24,0.30]	[0.35,0.37,0.39]	[0.24,0.28,0.30]	[0.90,0.93,0.95]
	X_6	[0.15,0.20,0.25]	[0.51,0.54,0.58]	[0.32,0.35,0.35]	[0.87,0.90,0.93]
S_3	X_7	[0.16,0.20,0.25]	[0.35,0.38,0.40]	[0.20,0.25,0.28]	[0.93,0.95,0.97]
	X_8	[0.14,0.20,0.25]	[0.30,0.34,0.36]	[0.21,0.24,0.28]	[0.95,0.97,0.99]
	X_9	[0.24,0.28,0.30]	[0.26,0.30,0.32]	[0.30,0.35,0.40]	[0.85,0.87,0.90]

Then, we need to standardize intuitive and fuzzy clouds decision matrix by means of the method in reference [12], and the attribute values of standardization are shown in Table 3.

Table 3. The Attribute Values of Standardization

attribute / new business		A_1	A_2	A_3	A_4
S_1	X_1	[0.81,0.88,1.0]	[0.84,0.88,1.0]	[0.68,0.79,1.0]	[0.91,0.97,1.0]
	X_2	[0.74,0.82,1.0]	[0.79,0.86,1.0]	[0.83,0.88,1.0]	[0.93,0.98,1.0]
	X_3	[0.71,0.80,1.0]	[0.90,0.94,1.0]	[0.71,0.83,1.0]	[0.93,0.97,1.0]
S_2	X_4	[0.70,0.79,1.0]	[0.82,0.90,1.0]	[0.70,0.78,1.0]	[0.96,0.98,1.0]
	X_5	[0.60,0.75,1.0]	[0.90,0.95,1.0]	[0.80,0.86,1.0]	[0.95,0.98,1.0]
	X_6	[0.60,0.75,1.0]	[0.88,0.94,1.0]	[0.91,0.91,1.0]	[0.94,0.97,1.0]
S_3	X_7	[0.64,0.80,1.0]	[0.88,0.92,1.0]	[0.71,0.80,1.0]	[0.96,0.98,1.0]
	X_8	[0.56,0.70,1.0]	[0.83,0.88,1.0]	[0.75,0.88,1.0]	[0.96,0.98,1.0]
	X_9	[0.80,0.86,1.0]	[0.81,0.87,1.0]	[0.75,0.86,1.0]	[0.94,0.97,1.0]

Calculate weighted clouds decision matrix:

$$[E_1]=\begin{bmatrix}0.349 & 0.443 & 0.390 & 0.575\\ 0.326 & 0.427 & 0.439 & 0.304\\ 0.318 & 0.467 & 0.391 & 0.577\end{bmatrix},[E_2]=\begin{bmatrix}0.314 & 0.468 & 0.389 & 0.586\\ 0.290 & 0.471 & 0.428 & 0.584\\ 0.290 & 0.490 & 0.458 & 0.585\end{bmatrix},$$

$$[E_3]=\begin{bmatrix}0.328 & 0.458 & 0.397 & 0.586\\ 0.296 & 0.438 & 0.397 & 0.586\\ 0.342 & 0.432 & 0.422 & 0.579\end{bmatrix},$$

$$[En_1]=\begin{bmatrix}0.162 & 0.241 & 0.282 & 0.165\\ 0.143 & 0.156 & 0.165 & 0.300\\ 0.138 & 0.176 & 0.144 & 0.172\end{bmatrix},[En_2]=\begin{bmatrix}0.137 & 0.150 & 0.141 & 0.171\\ 0.118 & 0.175 & 0.183 & 0.172\\ 0.118 & 0.161 & 0.183 & 0.172\end{bmatrix},$$

$$[En_3]=\begin{bmatrix}0.117 & 0.181 & 0.103 & 0.171\\ 0.080 & 0.165 & 0.129 & 0.171\\ 0.154 & 0.161 & 0.145 & 0.171\end{bmatrix}$$

$$[Hc_1]=\begin{bmatrix}0.083 & 0.088 & 0.076 & 0.102\\ 0.078 & 0.056 & 0.089 & 0.180\\ 0.056 & 0.065 & 0.066 & 0.132\end{bmatrix},[Hc_2]=\begin{bmatrix}0.074 & 0.042 & 0.078 & 0.131\\ 0.030 & 0.023 & 0.062 & 0.132\\ 0.030 & 0.036 & 0.044 & 0.132\end{bmatrix},$$

$$[Hc_3]=\begin{bmatrix}0.051 & 0.078 & 0.011 & 0.132\\ 0.023 & 0.072 & 0.026 & 0.132\\ 0.039 & 0.045 & 0.067 & 0.132\end{bmatrix}$$

The maximum and minimum values in weighted clouds decision matrix represent positive and negative reference points respectively.

$$\begin{cases}E_1^{+}=[0.349\quad 0.467\quad 0.439\quad 0.577]\\ E_1^{-}=[0.318\quad 0.427\quad 0.390\quad 0.304]\end{cases},\begin{cases}E_2^{+}=[0.314\quad 0.490\quad 0.458\quad 0.586]\\ E_2^{-}=[0.290\quad 0.468\quad 0.389\quad 0.584]\end{cases},$$

$$\begin{cases}E_3^{+}=[0.342\quad 0.458\quad 0.422\quad 0.586]\\ E_3^{-}=[0.296\quad 0.432\quad 0.397\quad 0.586]\end{cases}$$

$$\begin{cases}En_1^{+}=[0.162\quad 0.241\quad 0.282\quad 0.300]\\ En_1^{-}=[0.138\quad 0.156\quad 0.144\quad 0.165]\end{cases},\begin{cases}En_2^{+}=[0.138\quad 0.175\quad 0.183\quad 0.172]\\ En_2^{-}=[0.118\quad 0.150\quad 0.141\quad 0.171]\end{cases},$$

$$\begin{cases}En_3^{+}=[0.154\quad 0.181\quad 0.145\quad 0.171]\\ En_3^{-}=[0.080\quad 0.161\quad 0.103\quad 0.171]\end{cases}$$

$$\begin{cases}Hc_1^{+}=[0.083\quad 0.088\quad 0.089\quad 0.180]\\ Hc_1^{-}=[0.056\quad 0.056\quad 0.066\quad 0.102]\end{cases},\begin{cases}Hc_2^{+}=[0.074\quad 0.042\quad 0.078\quad 0.132]\\ Hc_2^{-}=[0.030\quad 0.023\quad 0.044\quad 0.131]\end{cases},$$

$$\begin{cases}Hc_3^{+}=[0.051\quad 0.078\quad 0.067\quad 0.132]\\ Hc_3^{-}=[0.023\quad 0.045\quad 0.011\quad 0.132]\end{cases}$$

The distances from each solution to positive and negative reference points are calculated through Formula (5) as shown in Table 4.

Table 4. Distance of Each Alternative from the Positive and Negative Ideal Solution

	$D(E_1^+)$	$D(E_1^-)$	$D(En_1^+)$	$D(En_1^-)$	$D(Hc_1^+)$	$D(Hc_1^-)$
X_1	0.0137	0.0814	0.0405	0.0405	0.0236	0.0084
X_2	0.0825	0.0123	0.0362	0.0408	0.0080	0.0093
X_3	0.0120	0.0825	0.0541	0.0054	0.0165	0.0093
	$D(E_2^+)$	$D(E_2^-)$	$D(En_2^+)$	$D(En_2^-)$	$D(Hc_2^+)$	$D(Hc_2^-)$
X_4	0.0181	0.0034	0.0122	1.4440e-005	3.0000e-004	0.0097
X_5	0.0090	0.0098	1.600e-005	0.0122	0.0063	0.0045
X_6	2.3040e-005	0.0181	0.0035	0. 0109	0.0086	0.0033
	$D(E_3^+)$	$D(E_3^-)$	$D(En_3^+)$	$D(En_3^-)$	$D(Hc_3^+)$	$D(Hc_3^-)$
X_7	0.0063	0.0258	0.0105	0.0049	0.0140	0.0082
X_8	0.0081	0.0015	0.0058	0.0066	0.0104	0.0077
X_9	0.0068	0.0021	0.0050	0.0105	0.0083	0.0140

Comprehensive prospect values of each solution were obtained by means of Formula (6) and (7), and three groups are sorted by means of the Step (4) to (6) in section of 3.2 as shown in Table 5.

Table 5. Comprehensive Cloud Prospect Values and Ranking Result of Alternatives

	V_E	V_{En}	V_{Hc}	V	**ordering**
X_1	-0.2085	-0.0372	0.0185	0.0523	1
X_2	0.0908	-0.0461	-0.0131	0.0380	2
X_3	-0.2160	0.0677	0.0040	-0.0390	9
X_4	0.0223	0.0207	-0.0369	-0.0257	8
X_5	-0.0124	-0.0465	-0.0013	-0.0091	6
X_6	-0.0658	-0.0303	0.0069	0.0240	3
X_7	-0.0701	0.0057	0.0026	-0.0102	7
X_8	0.0110	-0.0094	-0.0029	0.0067	5
X_9	0.0071	-0.0246	-0.0275	0.0169	4

From the above, the final order of these three groups is: $X_1 \succ X_2 \succ X_6 \succ X_9 \succ X_8 \succ X_5 \succ X_7 \succ X_4 \succ X_3$.

5. Conclusions

This paper proposed a multi-attribute group decision-making method for attribute values is cloud distribution and each expert is unable to assess all solutions according to cumulative prospect. Experts and solutions are classified with grouping rules and decision-making matrix is constructed by expectation, entropy and hyper entropy of cloud distribution. The value function is constructed with positive and negative reference points, then comprehensive cloud prospect values are obtained and plans are put in ordered. The experiment results show that the advantages of proposed method as follow:

(i) Comprehensive cloud prospect values are calculated by expectation, entropy and hyper entropy of cloud distributions. These properties not only describe randomness and fuzziness of uncertain information, but also give comprehensive cloud prospect values which make decision-making results more comprehensive and reasonable, and can decline investment risks effectively;

(ii) Proposed method can be applied in these situations: when only parts of the solution are evaluated by some experts and when all solutions are evaluated by each expert.

Further research based on this method is necessary, especially for investment decision-making, intelligent transportation and network planning.

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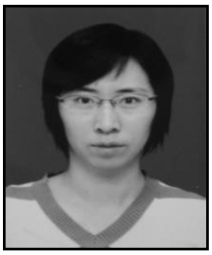

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