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A consensus model to manage the non-cooperative behaviors of individuals in uncertain group decision making problems during the COVID-19 outbreak

Xiaofang Li, Huchang Liao*, Zhi Wen
Business School, Sichuan University, Chengdu 610064, China

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ABSTRACT

The COVID-19 pandemic has brought lots of losses to the global economy. Within the context of COVID-19 outbreak, many emergency decision-making problems with uncertain information arose and a number of individuals were involved to solve such complicated problems. For instance, the selection of the first entry point to China is important for overseas flights during the epidemic outbreak given that reducing imported virus from abroad becomes the top priority of China since China has achieved remarkable achievements regarding the epidemic control. In such a large-scale group decision making problem, the non-cooperative behaviors of experts are common due to the different backgrounds of the experts. The non-cooperative behaviors of experts have a negative impact on the efficiency of a decision-making process in terms of decision time and cost. Given that the non-cooperative behaviors of experts were rarely considered in existing large-scale group decision making methods, this study aims to propose a novel consensus model to manage the non-cooperative behaviors of experts in large-scale group decision making problems. A group consistency index simultaneously considering fuzzy preference values and cooperation degrees is introduced to detect the non-cooperative behaviors of experts. We combine the cooperation degrees and fuzzy preference similarities of experts when clustering experts. To reduce the negative influence of the experts with low degrees of cooperation on the quality of a decision-making process, we implement a dynamic weight punishment mechanism to non-cooperative experts so as to improve the consensus level of a group. An illustrative example about the selection of the first point of entry for the flights entering Beijing from Toronto during the COVID-19 outbreak is presented to show the validity of the proposed model.

1. Introduction

Since the first discovery of the COVID-19 epidemic caused by a newly discovered coronavirus in December 2019, the world is facing unprecedented challenges [1]. After the outbreak of the epidemic, China immediately took effective measures to start the public health emergency mechanism to prevent the spread of the epidemic, and achieved remarkable achievements regarding the epidemic control [2]. To reduce the adverse effect of the epidemic, scholars have also studied the problems aroused during the outbreak of COVID-19. For example, Ren et al. [3] proposed a multiple attribute decision making method with hesitant fuzzy information to select drugs during the COVID-19 outbreak. Govindan et al. [4] put forward a decision support system based on doctor knowledge and a fuzzy inference system to alleviate the novel coronavirus pneumonia outbreak of traditional Chinese medicine supply chain outbreaks. Investigations regarding the impact of the COVID-19 epidemic on supply chains in various industries around the world were also conducted by different scholars [5–8]. Within the context of COVID-19 outbreak, many emergency decision-making problems with uncertain information arose and a number of individuals were involved to solve such complicated problems. For instance, at the time when the domestic epidemic situation of China has been obviously controlled, how to control imported cases becomes a new challenge for China. To reduce the risk of imported cases spreading in China, it is necessary to select appropriate entry points for overseas flights.

For such an important decision-making problem, multiple experienced experts need to be invited to participate in the decision-making process. For a decision-making problem, if the number of experts reaches 20, the decision-making problem can be regarded as a large-scale group decision making (LSGDM) problem [9]. Due to the large number of experts and the differences of their backgrounds, cultures and motivations, compared with the traditional group decision making (GDM) process, the LSGDM process faces more difficulties and challenges in terms...
of information loss [10], overconfidence of experts [11] and non-cooperative behaviors of experts [12]. When experts give initial evaluation values of alternatives, they may have uncertainty in the values due to their insufficient understanding on the alternatives. Within this context, fuzzy evaluation values are provided and the uncertainty of experts could be expressed by the confidence index [11]. To handle the overconfidence of experts in LSGDM, Liu et al. [11] proposed a consensus model based on fuzzy preference relations and self-confidence consensus levels to detect and manage the overconfident behaviors of experts. The non-cooperative behaviors of experts have a negative impact on the efficiency of a decision-making process in terms of the decision time and cost; however, they were rarely considered in large-scale GDM problems. Thus, this study aims to propose a method to manage the non-cooperative behaviors of experts in LSGDM problems.

Because a large number of experts are involved in the LSGDM process, the dimension reduction is deemed to be effective in deriving final results. At present, the frequently-used dimension reduction method is the clustering process. Various clustering algorithms have been used, such as the k-means clustering [13], fuzzy c-means clustering [14], hierarchical clustering [14] and grey clustering [15]. The k-means clustering algorithm requires to select a clustering center [16], and some outliers with excessive size may bring great influence. The computational complexity of the hierarchical clustering algorithm is high, and the algorithm is likely to cluster into chains. In contrast, the grey clustering algorithm clusters experts based on the similarities of experts, and the experts within a cluster have a high similarity but the experts in different clusters have significant differences. In this study, we consider the similarities of fuzzy preference values and cooperation degrees among experts. We use the grey clustering algorithm proposed by Liu et al. [11] to divide the experts whose fuzzy preferences and cooperation degrees are similar into a cluster.

In traditional GDM problems, it was assumed that experts are willing to accept the suggestions provided by the moderator, to modify their evaluation information in order to reach a group consensus. However, in practical decision-making problems, experts may be reluctant to accept the modification advices [17]. Dong et al. [18] presented a strategic weight manipulation to manage the non-cooperative behaviors of experts in the aggregation process of multiple attribute GDM. To reduce the negative impact of the non-cooperative behaviors of experts on the group decision quality, Xu et al. [19] put forward a mechanism to address the non-cooperative behaviors of individuals in GDM. The mechanism inserted an interaction step to the GDM process, which enabled experts to provide adjustment coefficients to manage the non-cooperative behaviors of experts. These models focused on the non-cooperative behaviors of experts in the aggregation process, while in the clustering process, they only considered the evaluation information of experts but ignored the differences of cooperation degrees of experts. The large differences in the cooperation degrees of experts in a cluster may have a negative impact on the quality of decision results. In other words, it is necessary to consider the evaluation information and cooperation degrees of experts simultaneously in the process of clustering.

Based on the above analysis, this study introduces fuzzy preference relations (FPRs) together with cooperative behavior relations (CBRs) to express the uncertain evaluations and cooperation degrees of experts simultaneously. A novel consensus reaching model which considers the non-cooperative behaviors of experts in LSGDM problems based on FPRs and CBRs is then developed. A group consistency index considering fuzzy preference values and cooperation degrees simultaneously is introduced to detect experts’ non-cooperative behaviors. We combine the cooperation degrees and fuzzy preference similarities of experts when clustering experts. It is noted that in the CRP proposed by Liu et al. [11], experts become more certain about the preference evaluation values they put forward after a feedback process, so their confidence values can be improved during the whole decision-making process. However, in the current study, the given cooperation degree does not change after experts present their preference evaluation values. In other words, experts do not need to participate in the feedback mechanism, which makes the decision-making process more efficient. In an LSGDM process, the importance of different experts may vary, depending on the levels of expertise they have. Considering that the non-cooperative behaviors of experts can affect decision results, we use a dynamic weight punishment mechanism to reduce the weights of the experts with low cooperation levels so as to improve the quality of results.

Bear the aforementioned points in mind, this study dedicates to introducing a consensus model which considers the non-cooperative behaviors of individuals in LSGDM problems based on FPRs and CBRs. The theoretical contributions of this study can be summarized as follows:

1. We present a novel consensus model to effectively address the non-cooperative behaviors of experts in LSGDM problems. Since different experts show different degrees of cooperation, we improve the consensus level of experts by supervising and managing their non-cooperative behaviors.
2. We divide the experts with high similarity degrees in terms of the preference evaluation information and cooperation levels into a cluster, which improves the rationality of clustering and makes the LSGDM process efficient.
3. We propose a dynamic weight punishment mechanism to reduce the adverse impact of non-cooperative experts on the quality of decision results. In this mechanism, the weights of experts are proportional to their degrees of cooperation, that is, the expert with a lower degree of cooperation has a lower weight.

Just as China has achieved remarkable results in epidemic control, the COVID-19 epidemic broke out in other countries. As an international exchange center, Beijing becomes the main battlefield for the prevention and control of imported COVID-19 (http://news.eastday.com/eastday/13news/auto/news/china/20200323/j7ai9173751.html). To prevent further importation into the capital, the choice of the first point of entry for flights from Toronto to Beijing is particularly important. We solve a case study concerning the selection of the first entry point of the Toronto flight into Beijing to prove the validity and practicability of the proposed LSGDM model.

The rest of this paper is organized as follows: Section 2 reviews relevant concepts used in this study, including the FPR, 2-tuple fuzzy linguistic representation and the state of the art of LSGDM. Section 3 demonstrates the proposed model in detail. Section 4 uses a practical example to show the practicability of the model. Section 5 provides some discussions and concluding remarks are presented in Section 6.

2. Preliminaries

Before introducing the consensus model, we present related preliminaries including the state of the art of LSGDM and the description of FPRs and CBRs. To facilitate the understanding of this study, mathematical symbols used in this study are summarized in Table 1.
2.1. The state of the art of large-scale group decision making

The GDM is a process in which a group of experts work together to make a decision for a certain problem towards a set of alternatives through a consensus reaching process (CRP). With the rapid developments of societal and technological paradigms and the increasing complexity of decision-making problems, more and more experts are invited to participate in the decision-making process to collect comprehensive and reliable information, and thus the LSGDM became significantly important and attracted many researchers’ attention [20–22]. Compared with the conventional GDM, the LSGDM faces many challenges [9].

Dimension reduction has been considered as an effective method to improve the efficiency for LSGDM. The clustering analysis [23] is a frequently-used dimension reduction method. Existing clustering methods can be divided into two categories: hierarchical clustering methods and partitioned clustering methods [24]. The difference between these two types of methods is whether they constitute clustering with data hierarchy. The former clustering methods can produce clusters with hierarchy but the calculation process is complex. According to the present research results, the partitioned clustering methods mainly include: the k-means clustering method [13], fuzzy c-means (FCM) clustering method [14] and fuzzy equivalence relation (FER) method [25]. In addition, inspired by the cloud computing, Wang et al. [26] improved the traditional hierarchical clustering method and introduced similarity degrees into the clustering process. In a social network analysis, Wu et al. [27] adopted the agglomerative clustering algorithm to detect community structures.

After a large group is divided into several clusters by clustering, the next step is to determine the weights of experts and clusters to reflect the importance of each expert [22]. For different LSGDM problems, multifarious methods have been generated to determine the weights of experts and clusters. For example, the majority principle has been applied to determine the weights of experts and clusters [27,28], which ignored individual differences and assumed that the importance of each expert is the same. Tang and Liao [9] combined the size and silhouette coefficient to reflect the importance of clusters. Rodriguez et al. [29] combined the scale and cohesion of clusters to determine the weights of clusters. The cohesion degree of clusters reflects the similarity of opinions among experts. The more similar the experts are, the more weight they carry. Ma et al. [30] determined the weights of sub-groups based on three factors regarding cluster certainty, similarity and scale. The weights determined by this method can well reflect the consistency among clusters and their status in decision making.

In this study, experts are divided into different clusters based on the similarities of cooperation degrees and fuzzy preferences among experts. Considering that the non-cooperative behaviors of experts can affect decision results, we propose a dynamic weight punishment mechanism to reduce the weights of the experts with low cooperation levels so as to improve the quality of results.

2.2. Fuzzy preference relations and cooperative behavior relations

In a decision-making problem, experts usually need to provide preference information over alternatives. The preference relation based on the pairwise comparisons over alternatives is a powerful tool to present experts’ preference information. The FPR [31] is a typical preference relation that has been used widely in uncertain decision-making problems [32,33]. For an LSGDM problem, let $X = \{x_1, x_2, \ldots, x_t\}$ be a set of alternatives. A reciprocal matrix $P = (p_{ij})_{n \times n}$ is called an FPR where $p_{ij}$ denotes the preference degree of alternative $x_i$ over alternative $x_j$ with $p_{ij} + p_{ji} = 1$, $\forall i, j$. $p_{ij} > 0.5$ denotes that alternative $x_i$ is preferred to alternative $x_j$; $p_{ij} < 0.5$ denotes that alternative $x_i$ is preferred to alternative $x_j$; $p_{ij} = 0.5$ denotes that alternative $x_i$ is as important as alternative $x_j$.

When experts give the values of fuzzy preference evaluations, they can also provide the corresponding cooperation degrees, which represent the belief degrees that the experts have regarding the given fuzzy preference values. For convenience, the experts can use a matrix $FC = (q_{ij})_{n \times n}$ to represent both values, and the matrix is called a fuzzy preference relation with cooperative behavior relation (FPR–CBR), where $q_{ij} \in [0, 1]$ represents the preference degree of alternative $x_i$ over alternative $x_j$, and $q_{ij} \in S^C$ represents the cooperation degree corresponding to $p_{ij}$. Since the cooperation degrees represent the subjective beliefs of experts’ cognition, it is adequate to use linguistic representation models to depict the CBRs of experts. In this study, we let $S = \{s_0 = None, s_1 = Very low, s_2 = Low, s_3 = Slightly low, s_4 = Medium, s_5 = Slightly high, s_6 = High, s_7 = Very high, s_8 = Perfect\}$ be a linguistic term set (LTS) to represent the cooperation levels of experts.

Example 1. Let $FC_a = \begin{bmatrix} (0.5, s_8) & (0.3, s_4) \\ (0.7, s_4) & (0.5, s_8) \end{bmatrix}$ be a decision matrix of expert $e_a$, where $0.3$ represents the preference value of alternative $x_1$ over alternative $x_2$, and $s_4$ denotes that the cooperation degree of expert $e_a$ on the preference value $p_{12} = 0.3$ is “medium”.

For two elements $(p_{ij,a}, q_{ij,a})$ and $(p_{ij,b}, q_{ij,b})$ of the FPR–CBRs $FC_a$ and $FC_b$, $p_{ij,a}$ and $q_{ij,a}$ respectively denotes the fuzzy preference value and its corresponding cooperation level of expert $e_a$, $p_{ij,b}$ and $q_{ij,b}$ respectively denotes the fuzzy preference value and its corresponding cooperation level of expert $e_b$. Inspired by Liu et al. [15], the following operations hold:

(i) $(p_{ij,a}, q_{ij,a}) + (p_{ij,b}, q_{ij,b}) = (\bar{P}_{ij,a} + p_{ij,b}, \min\{q_{ij,a}, q_{ij,b}\})$;

(ii) $(p_{ij,a} - q_{ij,a}) - (p_{ij,b} - q_{ij,b}) = (\bar{P}_{ij,a} - \bar{P}_{ij,b}, \min\{q_{ij,a}, q_{ij,b}\})$.

For an LTS $S = \{s_i | i = 0, 1, \ldots, t\}$, let $\beta \in [0, t]$ denote a number in the granularity interval of $S$ such that $i = round(\beta)$ and $\alpha = \beta - 1$. It follows $i \in [0, 1, \ldots, t]$ and $\alpha \in [0.5, 0.5)$. For the convenience of computation over the linguistic terms outside the LTS $S$, a 2-tuple linguistic representation model [34] was introduced with a function to make a transformation between the linguistic 2-tuple $(s_i, \alpha)$ and the numerical value $\beta$, such that

\[
\Delta(\beta) = (s_i, \alpha), \text{ with } \begin{cases} s_i, i = round(\beta), \\ \alpha = \beta - 1, \alpha \in [0.5, 0.5) \end{cases}
\]
where $\Delta$ is a one-to-one mapping function. For a 2-tuple $(s_i, \alpha)$, there is always an inverse function $\Delta^{-1}$ such that the 2-tuple returns its corresponding numerical value $\beta \in [0, 1]$: $\Delta^{-1} : S \times [-0.5, 0.5] \rightarrow [0, 1]$. Clearly, the conversion of a linguistic term in $S$ into a linguistic 2-tuple consists of adding a value zero as symbolic translation: $s_i \in S \Rightarrow (s_i, 0) = i$.

3. A consensus model for large-scale group decision making with non-cooperative behaviors

This section presents a consensus model which considers the non-cooperative behaviors of experts to solve LSGDM problems based on FPRs and CBRs. In Section 3.1, we use a clustering algorithm to divide experts into several subgroups based on the similarities of expert preferences. Section 3.2 introduces a method to determine the weights of experts and clusters. Section 3.3 presents a method for consensus measurement. Section 3.4 introduces a method to supervise and manage the non-cooperative behaviors of experts in LSGDM. Section 3.5 highlights the procedure of the consensus model.

3.1. The clustering process of experts

For an LSGDM problem, $E = \{e_1, e_2, \ldots, e_m\} (m \geq 20)$ denotes a group of experts who are invited to provide their evaluation information on a set of alternatives $\{x_1, x_2, \ldots, x_n\}$. In LSGDM, a clustering method can be used to divide the experts with high similarities into a subgroup. Since experts are classified into subgroups based on their similarity degrees, we use the grey clustering algorithm proposed by Liu et al. [15] for clustering.

Let $SM = (\rho_{q_{\alpha \beta}})_{m \times m}$ be a similarity matrix, where $\rho_{q_{\alpha \beta}}$ implies the similarity degree between expert $e_{\alpha}$ and expert $e_{\beta}$. It can be known from the grey clustering algorithm that: (1) If $\rho_{q_{\alpha \beta}} \geq \lambda$ where $\lambda \in [0, 1]$ is a threshold set in advance according to the actual situation, then, expert $e_{\alpha}$ and expert $e_{\beta}$ can be classified into a subgroup; (2) For a cluster $C_k$, if more than half of the experts in the cluster $C_k$ can be divided into a group with the expert $e_{\beta}$ according to the similarities between experts, the expert $e_{\beta}$ can be classified into cluster $C_k$.

To cluster the experts with high similarities efficiently, we can aggregate the evaluation values and cooperation degrees of experts. Firstly, each expert is required to provide an FPR–CBR $FC_e = (p_{i, j, \alpha}, q_{i, j, \alpha})_{n \times n}$ which can be divided into two small matrices $P_{\alpha} = (p_{i, j, \alpha})_{n \times n}$ and $Q_{\alpha} = (q_{i, j, \alpha})_{n \times n}$. The deviation between $P_{\alpha}$ and $Q_{\alpha}$ can be calculated by: $d(p_{\alpha}, q_{\alpha}) = \frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} |p_{i, j, \alpha} - q_{i, j, \alpha}|$ (2)

Then, the similarity degree between the FPRs of expert $e_{\alpha}$ and expert $e_{\beta}$ can be defined as:

\[ \rho_{P_{\alpha \beta}} = 1 - d(p_{\alpha}, p_{\beta}) \] (3)

Next, the deviation between $Q_{\alpha} = (q_{i, j, \alpha})_{n \times n}$ and $Q_{\beta} = (q_{i, j, \beta})_{n \times n}$ can be calculated by:

\[ d(q_{\alpha}, q_{\beta}) = \frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} |\Delta^{-1}(q_{i, j, \alpha}) - \Delta^{-1}(q_{i, j, \beta})| \] (4)

The similarity degree between the CBRs of expert $e_{\alpha}$ and expert $e_{\beta}$ can be defined as:

\[ \rho_{Q_{\alpha \beta}} = 1 - d(q_{\alpha}, q_{\beta}) \] (5)

Let $SM = (\rho_{q_{\alpha \beta}})_{m \times m}$ be a total similarity matrix that combines the similarity degrees of FPRs and CBRs of all experts. The total similarity $\rho_{q_{\alpha \beta}}$ between expert $e_{\alpha}$ and expert $e_{\beta}$ can be calculated by:

\[ \rho_{q_{\alpha \beta}} = \theta \rho_{P_{\alpha \beta}} + (1 - \theta) \rho_{Q_{\alpha \beta}} \] (6)

where $\theta$ is a parameter. A larger value of $\theta$ implies that the similarity degree of fuzzy preference values is more important than that of the cooperation levels in the clustering process.

Algorithm 1 is presented to facilitate the application of the proposed clustering method.

Algorithm 1 (A Clustering Method Based on FPR–CBRs).

Step 1: Collect the FPR–CBRs of experts. The experts present their own FPRs and CBRs individually.

Step 2: Calculate similarity degrees. Apply Eqs. (2) and (3) to calculate the similarity degree $\rho_{P_{\alpha \beta}}$ between the FPRs of expert $e_{\alpha}$ and expert $e_{\beta}$. Apply Eqs. (4) and (5) to obtain the similarity degree $\rho_{Q_{\alpha \beta}}$ between the CBRs of expert $e_{\alpha}$ and expert $e_{\beta}$. Then, we can obtain the total similarity $\rho_{q_{\alpha \beta}}$ by Eq. (6). If $\rho_{q_{\alpha \beta}} \geq \lambda$ ($\lambda \in [0, 1]$), then expert $e_{\alpha}$ and expert $e_{\beta}$ can be classified into a subgroup.

Step 3: For a cluster $C_k$ and expert $e_{\alpha}$, according to the similarities of experts, if more than half of the experts in the cluster $C_k$ can be divided into a group with the expert $e_{\beta}$, then, $e_{\beta}$ can be classified into the cluster $C_k$.

Through the above steps, $n$ experts can be divided into $k$ clusters. The experts in a cluster have high similarities and different clusters have great differences.

3.2. Weight determination for experts and clusters

After all experts are classified into $k$ subgroups, the weights of individual experts and subgroups should be determined, which is a key issue for LSGDM and directly affects the decision results. Commonly-used weight determination methods can be classified into subjective weighting methods, objective weighting methods and combined weighting methods [22].

In this study, we use the majority principle to determine the weights of experts. Since the similarities of the experts in a cluster are high after clustering, the weights of the experts in a cluster can be regarded as equal, and the clusters with more experts should be allocated higher weights. Thus, the weight $\omega_k$ of expert $e_{\alpha}$ in the cluster $C_k$ can be calculated as:

\[ \omega_k = \frac{1}{\text{num}_{C_k}}, \text{ for } k = 1, 2, \ldots, k \] (7)

where $\text{num}_{C_k}$ is the number of experts in the cluster $C_k$.

Next, we calculate the weight $\omega_k$ of the cluster $C_k$. Some methods have been proposed to calculate the weights of clusters [28]. In this study, we take the sum of the weights of experts in a subgroup as the weights of the cluster. In this sense, the weight of the cluster $C_k$ is:

\[ \omega_k = \frac{\sum_{k=1}^{\text{num}_{k}} \omega_k}{\sum_{k=1}^{\text{num}_{k}}} , \text{ for } k = 1, 2, \ldots, k \] (8)

3.3. Consensus measurement

Let $FC_{C_k}$ be an FPR–CBR of the cluster $C_k$, which can be obtained based on the weights of the experts in the cluster $C_k$. That is,

\[ FC_{C_k} = (p_{i, j, \alpha}, q_{i, j, \alpha})_{n \times n} = \sum_{\alpha=1}^{\text{num}_{C_k}} \omega_{\alpha} (p_{i, j, \alpha}, q_{i, j, \alpha}) \] (9)
Similarly, let $F_{C_{k}}$ be the global FPR–CBR, which can be calculated according to the weights of all clusters. That is,

$$Q_{C_{k}} = (p_{y_{i}C_{k}}, q_{y_{i}C_{k}})_{n 	imes n} = \sum_{k=1}^{k} \omega_{k} (p_{y_{i}k}, q_{y_{i}k})$$  \hspace{1cm} (10)

Then, the deviation between the cluster $C_{k}$ and the global group can be calculated as:

$$D \left( Q_{C_{k}}, Q_{G} \right) = (u, v)$$  \hspace{1cm} (11)

where

$$u = \frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} \left| p_{ij} - p_{ij,C_{k}} \right|$$  \hspace{1cm} (12)

$$v = \frac{2}{n(n-1)} \sum_{i=1}^{n} \sum_{j=1}^{n} \left| \Delta^{-} (p_{ij} - \Delta^{-} (p_{ij,C_{k}})) \right|$$  \hspace{1cm} (13)

Next, the consensus level $CL_{k}$ of the cluster $C_{k}$ can be determined as:

$$CL_{k} = \gamma (u - v) + (1 - \gamma) (1 - v)$$  \hspace{1cm} (14)

where $\gamma \in [0, 1]$ is a parameter that depends on the actual situation, reflecting the importance of FPRs against CBRs. $u' = 1 - u$ denotes the consensus level of FPRs and $v' = 1 - v$ denotes the consensus level of CBRs.

Similarly, the global consensus level $CL_{G}$ can be calculated by the weighted averaging operator over the consensus levels of all clusters. That is,

$$CL_{G} = \sum_{k=1}^{k} \omega_{k} \times CL_{C_{k}}$$  \hspace{1cm} (15)

It is obvious that $0 \leq CL_{G} \leq 1$. A threshold $\xi$ for $CL_{G}$ should be set in advance. If $CL_{G} \geq \xi$, then the global group reaches the acceptable consensus level; otherwise, a feedback mechanism is applied to improve the consensus level.

3.4. Non-cooperation behavior supervision and management

With the rapid development of information technology, people are increasingly connected with each other, which makes many decision-making problems have to involve experts from different areas to participate in the decision-making process. The number of experts has grown from a few to dozens or even hundreds. The more experts involved in decision-making, the more important it is to manage the decision behaviors of experts. Therefore, it is significant to improve the quality and efficiency of decision making by supervising and managing the non-cooperative behaviors of experts.

In practical LGSDM problems, it is difficult for clusters to guarantee a high similarity of cooperation degrees when fuzzy preference values are highly similar. Therefore, we supervise the non-cooperative behaviors of clusters by measuring their non-cooperative coefficients (NCC). The NCC of a cluster $C_{k}$ can be defined as:

$$NCC_{C_{k}} = 1 - \frac{v'_{C_{k}}}{CL_{G}}$$  \hspace{1cm} (16)

where $v'_{C_{k}}$ represents the consensus level of the cooperation degree of the cluster $C_{k}$. A smaller value of $v'_{C_{k}}$ leads to a larger value of NCC for the cluster $C_{k}$, which indicates that the contribution of the cooperation consensus of cluster $C_{k}$ to $CL_{G}$ is low.

To supervise the consensus levels of clusters, we need to supervise the non-cooperative behaviors of experts based on the consensus levels of fuzzy preference values and cooperation degrees. Let $\delta$ and $\epsilon$ be the thresholds of the consensus levels of fuzzy preference values and cooperation degrees, respectively. Comparing the consensus levels of fuzzy preference values and cooperation degrees with their corresponding thresholds, we may get four different cases:

1. $u_{i}^{'k} \geq \delta$ and $v_{i}^{'k} \geq \epsilon$, for $k \in \{1, 2, \ldots, k\}$;
2. $u_{i}^{'k} \geq \delta$ and $v_{i}^{'k} < \epsilon$, for $k \in \{1, 2, \ldots, k\}$;
3. $u_{i}^{'k} < \delta$ and $v_{i}^{'k} \geq \epsilon$, for $k \in \{1, 2, \ldots, k\}$;
4. $u_{i}^{'k} < \delta$ and $v_{i}^{'k} < \epsilon$, for $k \in \{1, 2, \ldots, k\}$.

For a cluster $C_{k}$, if $u_{i}^{'k} \geq \delta$ and $v_{i}^{'k} \geq \epsilon$, it means that the fuzzy preference values and cooperation degrees of the cluster $C_{k}$ reach the thresholds, and the cluster $C_{k}$ does not belong to a non-cooperative group. If one or both of the consensus levels of the fuzzy preference values and cooperation degrees of the cluster $C_{k}$ do not reach the thresholds, the group is considered to be a non-cooperative group. We can make a detailed analysis about the supervision of non-cooperative groups as follows:

(1) Non-cooperative behavior I

In this case, for a cluster $C_{k}$, the consensus level of fuzzy preference values does not reach the threshold, while the consensus level of cooperation degrees reaches the threshold, i.e., $u_{i}^{'k} < \delta$ and $v_{i}^{'k} \geq \epsilon$. It implies that the experts in the cluster $C_{k}$ have great differences in their fuzzy preference values of alternatives, but have a high cooperation degree in modifying the evaluation information of alternatives. These experts consider the problem from a global perspective; when their opinions differ from others, they are willing to modify their opinions in order to improve the consensus of the whole group. In general, these experts will not place barriers in the way of normal decision making.

(2) Non-cooperative behavior II

For a cluster $C_{k}$, if the consensus level of fuzzy preference values reaches the threshold while its consensus level of cooperation degrees fails to reach the threshold, i.e., $u_{i}^{'k} \geq \delta$ and $v_{i}^{'k} < \epsilon$, then, the experts in this cluster give their own evaluation information of alternatives with high similarities, relying on their rich experience and solid knowledge. But, once they give their evaluation values, they are reluctant to modify them.

(3) Non-cooperative behavior III

In this scenario, the consensus levels of fuzzy preference values and cooperation degrees in a cluster $C_{k}$ do not reach the corresponding thresholds set in advance, i.e., $u_{i}^{'k} < \delta$ and $v_{i}^{'k} < \epsilon$. That is to say, the experts in the cluster $C_{k}$ have great differences in fuzzy preference values of alternatives, and most of the experts stick to their own evaluation values out of self-esteem or their own understanding of the alternatives. These experts are reluctant to cooperate with the moderator to modify their evaluation values. In actual decision-making problems, these experts with low degree of cooperation will greatly reduce the efficiency and quality of the decision-making process. Hence, it is necessary to focus on the supervision and management of the non-cooperative behaviors of these experts.

Once all non-cooperative groups are detected, the next step is to manage and reduce their negative impact on the efficiency of the decision-making process. When the consensus levels of fuzzy preference values and cooperation degrees of the cluster $C_{k}$ reach their thresholds simultaneously, we do not need to manage this group again, and can make an aggregation over the evaluation values to deduce the final decision results. In case any one of the consensus levels of fuzzy preference values and cooperation degrees fail to reach their thresholds, the group is a non-cooperative group.
The management of these non-cooperative groups is described in detail below.

(1) Managing the non-cooperative behavior I

For the cluster with non-cooperative behavior I, we first determine the position of the preference value to be adjusted by:

$$\text{pos} = \{(i,j)|\max(D^- (q_{ij}, c_t))\}$$

(17)

If $p_{ik}^{(t)} > p_{ik}^{(t)}$, it means that the fuzzy preference value of the cluster at this position is relatively larger, compared with the corresponding value of the global group. Considering the high cooperation degree of the experts in the cluster, the moderator provides suggestions for modification to reduce the evaluation value of the cluster, making $p_{ik}^{(t)} = p_{ik}^{(t)}$. If $p_{ik}^{(t)} < p_{ik}^{(t)}$, it means that the fuzzy preference value of the cluster at the position is smaller than the corresponding value of the overall group. Since the experts in this cluster are willing to accept the moderator’s advice, to improve the overall consensus level, the preference evaluation value at this position could be increased such that $p_{ik}^{(t)} = p_{ik}^{(t)}$.

(2) Managing the non-cooperative behavior II

For the cluster with non-cooperative behavior II, the moderator does not need to propose modification suggestions from the perspective of the overall consensus. However, in view of their low cooperation degrees, we adopt a weight punishment mechanism to reduce the weight of the cluster. In this regard, the dynamic weights of clusters are updated as:

$$\sigma_k^{(t+1)} = \omega_k^{(t)} \left(1 - NCC_k^{(t)} \right) X, \quad \omega_k^{(t+1)} = \frac{\sigma_k^{(t+1)}}{\sum_{k=1}^{N} \sigma_k^{(t+1)}},$$

where $\chi \in [0, 1]$ is a parameter, reflecting the degree of punishment for non-cooperative groups. The lower the cooperation degree of the group is, the higher the value of $\chi$ is and the greater the punishment is.

(3) Managing the non-cooperative behavior III

In practical decision-making problems, clusters with non-cooperative behavior III may seriously prolong the decision time and increase the decision cost to affect the quality of the decision-making process. Therefore, effective methods should be adopted to manage it. Considering that the experts in such groups have low cooperation degrees, the above weight punishment mechanism is used to lower their decision status so as to reduce their impact on the quality of the decision results. In this sense, we use Eq. (18) to give them punishment weights. Since they are more noncooperative, they are punished heavily to reduce their influence on decision results.

3.5. The procedure to manage the non-cooperation behaviors of experts in LSGDM

In summary, we can manage the non-cooperative behaviors of experts in LSGDM problems by Algorithm 2.

Algorithm 2 (A Procedure to Manage the Non-cooperation Behaviors of Experts in LSGDM).

**Step 1:** Invite experts to express their preference values and cooperation levels through FPR–CBRs.

**Step 2:** Divide the experts into different clusters. According to the cooperation levels and fuzzy preference values, the experts with high similarities are classified into a cluster.

**Step 3:** Calculate the weights of each expert and cluster.

**Step 4:** Compute the consensus degrees of each cluster.

**Step 5:** Check the consensus degrees. If the consensus degrees of a cluster do not meet the corresponding thresholds set in advance, different feedback mechanisms corresponding to different non-cooperative behaviors are used to provide modification suggestions to the experts so as to improve the group consensus levels. After all clusters reach the given thresholds, we then proceed to the next step.

**Step 6:** Select the best alternative based on the modified evaluations of experts.

To make it easy to understand our model, the framework of the proposed model is displayed in Fig. 1.

4. Case study: Selecting the first point of entry for flights during the COVID-19 outbreak

This section illustrates the feasibility and practicability of the proposed consensus model through a case study on the selection of the first point of entry for flights entering Beijing from Toronto, Canada during the COVID-19 outbreak.

4.1. Case description

Since the middle of December 2019, cases of pneumonia of unknown cause have been found in Wuhan, Hubei Province, China, with the main symptoms including fever, fatigue, cough and shortness of breath [35]. With the spread of the epidemic, such cases have also appeared in other parts of China and abroad. Upon investigation, it was found that the culprit was a novel coronavirus, a pneumonia caused by a novel infection called COVID-19 [36]. Since the outbreak of the epidemic, the Central Party Committee and the State Council of China have attached great importance to it. To prevent the epidemic from spreading, the Central Committee of China has set up a leading group on epidemic response. In addition, provinces and cities in China have taken effective measures and launched a public health emergency response mechanism to win the epidemic war [2].

In the process of outbreak, China has experienced the following five stages: (1) quickly response to the sudden outbreak, (2) preliminary curb the momentum of the spread, (3) gradually increased the number of cases down to single digits, (4) decisive battle in Wuhan, Hubei province defensive war results, and (5) national epidemic prevention and control into the normalized situation (http://www.chinanews.com/gn/2020/06-07/9205498.shtml). So far, China’s epidemic prevention and control has achieved a phased victory. If the fight against the new champions league is a big battle, then, China has entered the stage of tied up; but the outbreak of world war has just begun from a global perspective. On March 13, 2020, the World Health Organization (WHO) announced that Europe has become a global epidemic area (https://www.sohu.com/a/379957110_464387). For China, reducing the impact of the European and North American epidemic on the domestic epidemic has become a top priority.

As an international exchange center, Beijing has become the main battlefield for the prevention and control of imported COVID-19 cases. Civil aviation is the main mode of international personnel movement. As an important international aviation hub in China, the Beijing Capital International Airport has nearly 200 international passenger flights every week from 33 countries including the United States, South Korea, France, Germany and Canada. The capital airport faces unprecedented pressure regarding the imported epidemic risk, and it has become the forefront of the war. With the approval of the State Council, it was decided to adjust the destinations for the Beijing international flights from the first entry point of entry. This measure can control the continuous import of foreign epidemic cases into Beijing, which is conducive to ensuring the safety and health of international passengers entering Beijing (http://news.eastday.com/eastday/13news/auto/news/china/20200323/7a19173751.html). In this regard, the selection of the first point of entry for flights is an important decision-making problem during the COVID-19 outbreak.

...
To choose the first point of entry, an airline company invites 20 experts to evaluate four alternative cities: 
\(x_1\): Choose to enter China from Tianjin;
\(x_2\): Choose to enter China from Chengdu;
\(x_3\): Choose to enter China from Taiyuan;
\(x_4\): Choose to enter China from Changsha.

These twenty experts provide their fuzzy preference evaluation values and cooperation levels. Then, twenty matrices are formed as follows:

\[
FC_1 = \begin{bmatrix}
(0.5, s_8) & (0.8, s_7) & (0.7, s_6) & (0.7, s_7)
\end{bmatrix}
\]

\[
FC_2 = \begin{bmatrix}
(0.2, s_7) & (0.5, s_8) & (0.6, s_6) & (0.4, s_7)
\end{bmatrix}
\]

\[
FC_3 = \begin{bmatrix}
(0.3, s_6) & (0.6, s_6) & (0.5, s_8) & (0.7, s_6)
\end{bmatrix}
\]

\[
FC_4 = \begin{bmatrix}
(0.5, s_8) & (0.6, s_7) & (0.7, s_6) & (0.5, s_8)
\end{bmatrix}
\]

\[
FC_5 = \begin{bmatrix}
(0.7, s_7) & (0.5, s_6) & (0.7, s_7) & (0.4, s_8)
\end{bmatrix}
\]

\[
FC_6 = \begin{bmatrix}
(0.6, s_6) & (0.3, s_7) & (0.5, s_6) & (0.4, s_6)
\end{bmatrix}
\]
The specific implementation steps are as follows. Step 1 has been completed.

$$C = \{\theta = 0.84, \xi = 0.8\}$$

Step 3: Calculate the weights of experts and clusters. We use Eqs. (7) and (8) to obtain the weights of experts and clusters, respectively. The results are shown in Table 2.

Step 4: Calculate the consensus level. We use Eq. (11) and the obtained weights to calculate the global FPR-CBR, and the result is as follows:

$$C_0 = \{(0.5, s_8), (0.54, s_4), (0.48, s_3), (0.61, s_2)\}$$

In this study, we set $\gamma = 0.6$ and $\xi = 0.84$. Eqs. (12) and (13) are used to determine the consensus levels of fuzzy preference values and cooperation degrees. We use Eqs. (14) and (15) to calculate the consensus levels of clusters and the global group. The results are shown in Table 3.

It can be seen from Table 3 that the consensus level of the global group does not reach the threshold $\xi = 0.84$. We then supervise and manage the non-cooperative groups.

Step 5: Supervise and manage the non-cooperative clusters. Here, we set $\delta = 0.9$ and $\epsilon = 0.8$. Comparing the consensus levels of fuzzy preference values and cooperative degrees of each cluster with the corresponding thresholds, we determine whether the cluster is a non-cooperative cluster. The supervision results of the non-cooperative behaviors of clusters are shown in Table 4.

The consensus levels of cooperation degrees of clusters $C_1, C_2$, and $C_3$ are lower than the threshold, so the experts in these clusters are less willing to modify their opinions in the LSGDM process. The weights of these clusters should be reduced according to the weight punishment mechanism. By Eq. (16), we can obtain $NCC_0$, and calculate the updated weights of clusters. The results are shown in Table 5.

Although the consensus levels of clusters $C_3$ and $C_4$ do not reach the threshold of fuzzy preference values, the cooperation levels of these clusters are high and the experts in these two clusters are willing to modify their opinions to improve the global consensus. Thus, Eq. (18) is used to determine the position $(i, j)$ that should be adjusted in clusters $C_3$ and $C_4$. For cluster $C_3$, $\max (\Delta (q_{0, C_3})) = 3$, the corresponding positions to be adjusted are $(1, 3), (2, 3)$, and $(3, 4)$. For cluster $C_4$, the corresponding
After modification, the global matrix \( FPR–CBR \) is

\[
\begin{bmatrix}
0.5, s_8 & 0.53, s_1 & 0.46, s_1 & 0.59, s_2 \\
0.47, s_1 & 0.5, s_8 & 0.48, s_3 & 0.47, s_3 \\
0.54, s_3 & 0.52, s_3 & 0.5, s_8 & 0.56, s_2 \\
0.41, s_2 & 0.53, s_3 & 0.44, s_2 & 0.5, s_8 \\
\end{bmatrix}
\]

Table 3:
The consensus levels of clusters.

| C_1 | C_2 | C_3 | C_4 | C_5 |
|-----|-----|-----|-----|-----|
| \( \omega_{C_1} \) | 0.25 | 0.30 | 0.15 | 0.10 | 0.20 |
| \( \omega_{u} \) | 0.20 | 0.17 | 0.33 | 0.5 | 0.25 |

Table 4:
The supervision of the non-cooperative behaviors of clusters.

| C_1 | C_2 | C_3 | C_4 | C_5 |
|-----|-----|-----|-----|-----|
| \( u^t \) | 0.922 | 0.923 | 0.872 | 0.825 | 0.917 |
| \( u^v \) | 0.604 | 0.667 | 1 | 0.896 | 0.604 |
| \( CL_{C_1} \) | 0.795 | 0.821 | 0.923 | 0.853 | 0.792 |

Table 5:
The updated weights of clusters.

| C_1 | C_2 | C_3 | C_4 | C_5 |
|-----|-----|-----|-----|-----|
| \( NCC_{C_1} \) | 0.270 | 0.193 | 0 | 0 | 0.270 |
| \( \omega_{C_1} \) | 0.237 | 0.298 | 0.166 | 0.111 | 0.188 |

The matrices of the adjusted clusters are

\[
FC^C_{C_1} = \begin{bmatrix}
(0.5, s_8) & (0.6, s_1) & (0.48, s_3) & (0.77, s_2) \\
(0.4, s_1) & (0.5, s_8) & (0.48, s_3) & (0.42, s_3) \\
(0.52, s_3) & (0.5, s_8) & (0.5, s_8) & (0.5, s_2) \\
(0.23, s_2) & (0.58, s_3) & (0.5, s_2) & (0.5, s_9) \\
(0.5, s_8) & (0.35, s_1) & (0.45, s_3) & (0.61, s_4) \\
\end{bmatrix}
\]

\[
FC^C_{C_2} = \begin{bmatrix}
(0.5, s_8) & (0.53, s_1) & (0.46, s_3) & (0.59, s_2) \\
(0.47, s_1) & (0.5, s_8) & (0.48, s_3) & (0.47, s_3) \\
(0.54, s_3) & (0.52, s_3) & (0.5, s_8) & (0.56, s_2) \\
(0.41, s_2) & (0.53, s_3) & (0.44, s_2) & (0.5, s_8) \\
\end{bmatrix}
\]
The adjusted consensus levels of the clusters.  
Table 6  
| $C'_{L}$ = 0.840 = $C'_{L}$ |
|---|---|---|---|---|---|
| $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ |
| 0.910 | 0.920 | 0.940 | 0.910 | 0.910 |
| 0.604 | 0.667 | 1 | 0.896 | 0.604 |
| 0.790 | 0.820 | 0.960 | 0.900 | 0.790 |

Then, the updated consensus levels can be calculated as shown in Table 6. Since $C_{L} = 0.840$, it means that the global group reaches an accepted consensus.

After the iteration process, the consensus degree of clusters has been significantly improved through the detection and management of the non-cooperative behaviors of experts. To show the improvement process visually, we demonstrate the consensus degrees in the iterative process in Fig. 2.

It can be seen from Fig. 2 that after one iteration, the consensus degree of the fuzzy preference values of the experts in cluster $C_3$ and cluster $C_4$ has been significantly increased and the cooperation degree of experts remains unchanged. This means that it is meaningful to manage the non-cooperative behaviors of experts in a cluster with low consensus.

**Step 6:** Select the optimal alternative.

Based on the final matrix, we can get the final ranking as $x_3 > x_1 > x_4 > x_2$. Thus, the optimal point of entry is $x_3$.

Inspired by the clustering method proposed by Liu et al. [11], we classified the experts into different sub-groups based on the similarities of fuzzy preference values and cooperation degrees. After classification, the differences of the experts within a cluster are small, while the differences of the experts between clusters are large. Experts put forward the fuzzy preference values and propose the corresponding degrees of cooperation at the same time. In this way, different experts show a big difference in cooperation degrees according to their own acknowledgment. In this sense, it is effective to cluster experts when dealing with the non-cooperative behaviors of experts in LSGDM. For the clusters with low consensus levels of cooperation degrees, applying the weight punishment mechanism to manage the non-cooperative behaviors of experts can effectively improve the overall consensus level. The illustrative example verified the effectiveness and practicability of the model in solving practical problems.

5. Comparisons and discussions

5.1. Comparative analyses

We then discuss the advantages of the proposed consensus model in dealing with the non-cooperative behaviors of experts in LSGDM based on the comparisons with other relevant methods.

(1) Dong et al. [18,37] also focused on the supervision and management of non-cooperative behaviors of experts in GDM problems. However, the method proposed by Dong, Zhang and Herrera-Viedma [37] is limited to solve the non-cooperative behaviors of experts for GDM problems involving a few experts. In contrast, our consensus model can be used to solve the non-cooperative behaviors of experts in GDM problems in which many experts participate. In addition, Dong et al. [18] only considered the non-cooperative behaviors of experts in the integration stage, while we take into account the non-cooperative behaviors of experts in the integration and selection process. In the clustering process, the experts with high similarities are divided into a cluster by combining the similarities of fuzzy preference values and cooperation degrees. In the calculation of consensus degree, the consensus levels of clusters are determined by combining the consensus levels of fuzzy preference values and cooperation degrees. Through comparison, it can be found that in the clustering process, if experts are clustered based on two similarity indexes of fuzzy preference values and cooperation degrees, the experts in a cluster have higher similarity, and the experts from different clusters have greater differences.

(2) Xu, Zhang and Chen [38] proposed a consensus model which managed the non-cooperative behaviors of experts based on social network relationships and preference risks. This model divided large-scale experts into different modules based on the trust relations between experts by the Louvain method. Our model introduced the non-cooperative degrees of experts in the process of dimensionality reduction. Although the trust value between experts in a module is high, compared with the clustering results of our proposed model, the cooperation degrees of experts in this module are different.

5.2. Theoretical and managerial implications

On the one hand, the experts with different background knowledge and experience will show different degrees of cooperation in decision making. When more decision-makers participate in a decision-making process, the non-cooperative behaviors of experts will have a negative impact on the quality of decision results. In other words, the quality can be effectively improved by supervising and managing the non-cooperative behaviors of experts. When detecting the non-cooperative behaviors of experts, we cluster experts into sub-groups based on the similarities of fuzzy preference values and cooperation degree values. The similarities of the fuzzy preference values and cooperation degree values of the experts in a cluster are high, but the differences of the fuzzy preference values and cooperation degree values of the experts in different clusters are large. This result is in line with the significance of clustering.

On the other hand, at the time when the domestic fight against the COVID-19 epidemic achieved remarkable results, the prevention of imported cases from abroad becomes the top priority for China. In this case, choosing the best first entry point to China for overseas flights during the epidemic period can effectively prevent the spread of imported cases in China. Therefore,
Table A.1

| Function Rp = calfpw(Fp, numexp) |
|----------------------------------|
| Rp = 1.0;                        |
| for i = 1 to numexp:             |
|     for j = 1 to numexp:         |
|         d(i,j) = 1 - 2 * sum / (numexp * (numexp - 1)); |
|     end                           |
| Rp = d;                          |

6. Conclusions

This paper introduced a consensus reaching model which takes into account the non-cooperative behaviors of experts in LSGDM problems based on FPRs and CBRs to solve the problem of first entry point selection during the COVID-19 epidemic outbreak. The model is mainly composed of four parts: clustering experts, weight determination of experts and clusters, consensus measurement, and management of non-cooperative behaviors. We demonstrated the usefulness of the proposed model by a case study of the selection of the first point of entry for flights entering Beijing from Toronto during the COVID-19 outbreak. In this study, all experts were supposed to adopt FPRs to provide evaluation information for alternatives.

It should be noted that we investigate the model in a case study with a simulation of the case data. Thus, it would be more interesting to implement the method in practical decision making problems. In actual GDM problems, some experts may provide the evaluation information by other information expression tools, such as the probabilistic linguistic preference relations. Compared with FPRs, the probabilistic linguistic preference relation can express experts’ opinions more comprehensively and completely. In the future, we will continue to study the supervision and management of the non-cooperative behaviors of experts in LSGDM under the probabilistic linguistic environment. In addition, this paper assumed that experts are independent; however, in choosing the first entry point of flight or other decision-making problems that need to consider the non-cooperative behaviors of experts, there may be some social relationships between experts. These social relationships may affect the decision results. It would be an interesting topic to study the non-cooperative behaviors of experts in LSGDM based on the trust relationship between experts.

CRediT authorship contribution statement

Xiaofang Li: Conceptualization, Data curation, Formal analysis, Writing - original draft. Huchang Liao: Conceptualization, Funding acquisition, Supervision, Writing - review & editing. Zhi Wen: Formal analysis, Validation, Visualization, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Table A.2
The code of numerical calculation in MATLAB.

```matlab
% 参数的初始化
% 输入数据—模糊相关度矩阵
X = [0.5 0.8 0.7 0.7; 0.2 0.5 0.6 0.4; 0.3 0.6 0.5 0.7; 0.3 0.8 0.5 0.2];
Y = [0.6 0.4 0.7 0.6; 0.4 0.5 0.7 0.4; 0.3 0.5 0.8 0.3; 0.4 0.8 0.7 0.3];
Z = [0.6 0.8 0.6 0.3; 0.7 0.3 0.7 0.4; 0.6 0.2 0.5 0.4; 0.3 0.8 0.6 0.3];
% 输出结果—相似度矩阵
similarity_matrix = [0.5 0.9 0.7 0.8; 0.3 0.5 0.8 0.6; 0.2 0.4 0.6 0.5; 0.4 0.8 0.7 0.6];

% 定义参数—输入数据
theta = 0.5; % 计算相关性的参数
mu = 0.9; % 模糊隶属度的参数
mu_max = 0.9; % 计算模糊矩阵的大小
% 计算模糊偏好相关度
R = calsfpw(FcCo, mu, t);
% 计算合作度相关度
R2 = calscd(FcCo, mu, t);
% 计算总体相似度
R3 = theta * R + (1 - theta) * R2;
```

Table A.3
The similarity matrix of the fuzzy preference values of experts.
Table A.4
The similarity matrix of the cooperation degrees between experts.

Table A.5
The total similarity matrix between experts.

Table A.6
The final decision matrix of experts.

Appendix
Some snapshots of programming code that calculates the similarities of fuzzy preference values and cooperation values are shown in Tables A.1–A.6.

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