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Managing non-cooperative behaviors in consensus reaching processes: a comprehensive self-management weight generation mechanism

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Abstract

In group decision-making, a consensus-reaching process (CRP) is critical to minimize conflicts among decision-makers. Non-cooperative behaviors during the CRP may slow the consensus achievement or even lead to consensus failure. Previous research has not thoroughly identified various non-cooperative behaviors nor has it developed distinct management strategies for different CRP stages. This study aims to provide a systematic approach for identifying and addressing non-cooperative behaviors at different CRP stages, employing tailored management for each behavior type. We introduce and apply a concept named 'comprehensive score' to facilitate varied responses to non-cooperative behaviors throughout the CRP. A null-norm operator-based self-management weight generation mechanism is proposed to monitor experts' historical performance, while a systematic analysis of experts' characteristics enables detailed classification of non-cooperative behaviors. Through the research, we find that there are seven types of non-cooperative researches which needs to be respectively addressed according to its effects. The proposed management scheme improves the efficiency of CRP. Besides, the current research enriches the mechanisms for identifying and handling non-cooperative behaviors. It offers methodological references for non-cooperative behaviors management in more complex decision-making scenarios.

Keywords Group decision making · Consensus reaching process · Non-cooperative behaviors · Preference relation

1 Introduction

Group decision making (GDM) is common in various domains of life and work [1, 2]. The GDM process typically involves collecting a broad range of preferences from a group of experts, followed by an aggregation process and an exploitation process to determine the best solution. Various aggregation methods are employed to gather individual opinions, and the most preferred option is selected based on the group's aggregated opinion [3]. Since conflicts may arise during GDM, a consensus-reaching process (CRP) is necessary to ensure that the decision outcome is accepted by the group [4]. In the traditional definition of CRP, experts are required to achieve complete consensus on preferences, which is known as "hard consensus" [5]and is extremely difficult to achieve in real-world setting. Recognizing the complex uncertainties inherent in real-life GDM, the concept of "soft consensus" was introduced [6], in which the CRP only necessitates that the consensus degree reaches a predetermined value. This approach is much more practical and achievable than complete consensus in most real-world GDM situations. During the past few decades, researches on CRP have been carried out from different aspects. For instance, Zhang et al. [7] constructed minimum adjustment and personalized individual semantic based consistency improving models to accelerate the CRP. Li et al. [8] discussed the CRP in multi-criteria social network GDM.

Due to varying levels of expertise, knowledge background, social status, and economic position, not all experts

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are willing to contribute to the consensus, and some may refuse to change their initial preferences towards the consensus due to personal interests, resulting failing processes and in time-consuming CRPs [9]. Hence, it seems adequate to manage such non-cooperative behaviors to avoid previous problems. So far, researchers have developed various management schemes. Quesada et al. [10] proposed a management scheme based on a uninorm operator to reduce the weights of non-cooperative experts. Gou et al. [11] used double hierarchy (DHLPR) clustering and expert ratings to reduce the weight of non-cooperative experts and introduced a consensus-reaching model to address three types of non-cooperative behaviors. Palomares et al. [12] defined a fuzzy clustering scheme to address non-cooperative behavior in individuals and subgroups. Chao et al. [13] introduced a consensus method based on similarity measures of heterogeneous preferences and a weighting process to manage non-cooperative behavior in large-scale group decision-making. Du et al. [14] summarized four punishment approaches for non-cooperative behavior and proposed an independent consensus-reaching model, which was combined with a supervised consensus-reaching model to create a mixed model for managing non-cooperative behavior. Mandal et al. [15] applied a grey clustering method and defined the non-cooperative degree using a cluster consensus index and a group consensus index to manage non-cooperative behavior. Dong et al. [16] categorized non-cooperative behavior into three different classes and presented a mechanism for dynamically generating weights of experts using multi-attribute mutual evaluation matrices (MMEMs) provided by experts in the proposed consensus model. Later, Dong et al. [17] extended the behavior management scheme to address non-cooperative behavior in large-scale group decision making(LSGDM). Li et al. [18] combined the similarity of preferences and the degree of cooperation to cluster experts and proposed a dynamic weight punishment mechanism for non-cooperative experts to make the weight proportional to the degree of cooperation. Xu et al. [19] developed a consensus model for large-group emergency decision-making, which addressed non-cooperative behavior and minority opinions. Tian et al. [20] applied social network analysis to develop a consensus framework for managing non-cooperative behavior. Despite the significant amount of research on managing non-cooperative behavior, it is important to point out that previous works have several limitations.

1. In most studies, non-cooperative behavior in different stages and periods of the CRP has been addressed in the same manner, despite the fact that non-cooperative behavior in later rounds may pose a more substantial threat to consensus reaching.
2. The weight determination scheme based on non-cooperative behavior in CRPs is typically presented based on the performance of individuals or sub-groups in a single moment or round. However, the emergence of non-cooperative attitudes is often traceable over time. The existing weight generation scheme based on a mutual evaluation matrix [16] only considers the expert's performance in a single moment or round, which may result in the loss of valuable information.
3. The current identification of non-cooperative behaviors is oversimplified and does not fully capture the complexity of practical CRPs, limiting the validity and reliability of GDM results.

To address these limitations, we propose a mutual evaluation matrix-based consensus model, which works in conjunction with a self-management weight generation scheme to distinguish experts' non-cooperative behavior at different periods. Additionally, a systematic identification scheme of non-cooperativeness is introduced to facilitate different treatments regarding different behaviors.

The proposed approach introduces several novel contributions:

1. A comprehensive score that distinguishes the effect of non-cooperative behavior in different CRP stages and periods. This score is calculated by applying a specific function on the mutual evaluation matrix provided by experts. By incorporating the comprehensive score, non-cooperative behavior in different periods can be addressed differently, and mutual evaluations can be applied more comprehensively.
2. To ensure that the consensus decision result is more reliable, we propose a null-norm operator based on the mutual evaluation matrix to determine experts' weights, which considers not only their performance in a single round but also their previous performance during the CRP.
3. It is also proposed a systematic identification scheme for non-cooperative behavior in a CRP, considering factors such as cooperative attitude, reliability, professional level, ability, fairness, not over-collaboration, and not conspiracy of experts. A corresponding self-management weight determination strategy is presented to manage different types of behavior in different ways. This non-cooperative behavior management scheme is integrated with a new consensus model.

To illustrate the feasibility of the proposed consensus model cooperates with the novel non-cooperative behaviors identification and management scheme, it is applied to deal with the fresh logistics enterprises selection problem. Comparative analysis with existing literature has been carried out from both theoretical and numerical aspects.

The remaining parts of this study are as follows: Section 2 introduces some basic concepts related to the proposal. Section 3 proposes a comprehensive self-management weight generation scheme in CRP, and the consensus resolution framework. Section 4 clarifies how to identify and deal with different non-cooperative behaviors, comparative analysis with existing researches is conducted. Section 5 presents the CRP algorithm with non-cooperative behavior management scheme. In Section 6, a case study is presented to show the performance of the proposal, and finally Section 7 points out some conclusions and future works.

2 Preliminairies

Before introducing the consensus model and non-cooperative behaviors classification and management mechanism, we present some basic knowledge which are closely related to the current research, such as GDM, CRP, and null-norm operator.

2.1 Group decision making

GDM problems widely exist in human-being's daily life. In a GDM problem there are more than one participant involved to select the best alternative from an alternative set, or to select the best solution from a set of solutions to the problem. Formally, a GDM problem consists of: [1]: (1) A set of alternatives/solutions $X = \{x_1, x_2, ..., x_n\}$, in which the best one needs to be chosen according to a certain decision scheme. (2) A set of experts $E = \{e_1, e_2, ..., e_m\}$, who are usually experts in the field of GDM, will provide evaluations/preference upon the alternatives or solutions. If every expert provides his/her preference over one alternative upon another, all preferences can be collected by means of a $n \times n$ preference matrix. If the expert provides preferences under the framework of fuzzy set theory [21], the preferences could be gathered to form a fuzzy preference relation matrix, which has been widely applied to deal with uncertain information in GDM.

Definition 1 *[22] Suppose that $X = \{x_1, x_2, \cdots, x_n\}$ is the alternative set, P_i is the fuzzy preference relation provided by expert e_i, it forms a set of fuzzy sets on $X \times X$, which can be characterized by a membership function $\mu_{P_i} : X \times X \rightarrow [0, 1]$. If n is a finite value, P_i can be written as below.*

$$P_i = \begin{pmatrix} - & \ldots & p_i^{1n} \\ & \ddots & \vdots \\ p_i^{n1} & & - \end{pmatrix}$$

where $p_i^{lk} = \mu_{p_i}(x_l, x_k) \in [0, 1]$ is the preference of alternative x_l over x_k, $l, k \in 1, \ldots, n, l \neq k$. Here, $p_i^{lk} < 0.5$ indicates that e_i prefer x_k over x_l, $p_i^{lk} > 0.5$ indicates that e_i prefer x_l over x_k, $p_i^{lk} = 0.5$ indicates that for e_i, the preference of x_k and x_l is the same. In the current work, in order to better deal with the consistency preference relations, we assume that the fuzzy preference relations satisfy the addition consistency property, i.e., if $p_i^{lk} = x, x \in [0, 1], l \neq k$, then $p_i^{kl} = 1 - x$.

A traditional GDM process contains two main steps: (1) Aggregation of the preferences provided by experts, by selecting and applying some aggregation operators; (2) Exploitation of the most appropriate alternative, by applying some selection criterion. The exploitation result can be a single alternative or a subgroup of the alternatives.

2.2 Consensus reaching process

In traditional GDM, the solution obtained from the gathered opinion may not satisfy all experts, since some of them may feel that their own preferences have been ignored [10]. A CRP is necessary, to decrease this feeling in GDM, by setting a negotiation process among experts before the selection process, which makes the decision result closer to expectation of experts. CRP is a dynamic evolution process, which is usually reached after several rounds of discussion. The moderator in a consensus model takes responsibility for the supervision and regulation of the whole consensus process. Reaching a consensus needs the support of each expert, who collaborates with each other, has the ability to modify the preference according to the feedback, and willing to find an appropriate solution for the group. A CRP mainly includes the following steps [23]:

(1) *Preference gathering*

Every expert e_z is requested to provide his/her preferences upon all alternatives, in form of fuzzy preference relations, or other various forms.

(2) *Consensus degree measurement*

There are different ways to determine the consensus degree, for instance, based on the use of similarity or distance measures of experts' preferences, to obtain the consensus degree of the group. The consensus degree cr is usually a value in the interval [0, 1].

(3) *Consensus control*

A pre-established threshold $\mu \in [0, 1]$ is applied to determine if the consensus is reached or not. If $cr \geq \mu$, we say that consensus has been reached among the experts, then the selection process should be carried out. Otherwise, another round of adjustment should be carried out. In order to avoid too many rounds of discussion, a maximum number of discussion rounds is set as $Maxround \in \mathbf{N}$.

(4) *Feedback generation*

During the CRP, the individual preferences of the experts will be gathered to form a collective preference P_c. The experts whose preferences are farthest from the collective one should be identified, and modified to increase the consensus degree in the following rounds.

2.3 Nullnorm operator

Nullnorm operator was first proposed in 2001 [24]. This operator combines relevant properties of t-norms and t-conorms, and it has been successively applied in various practical fields.

Definition 2 *[25] A nullnorm operator is a function $NU : [0, 1] \times [0, 1] \rightarrow [0, 1]$, which satisfies the following properties:*

- *Commutativity: $NU(x, y) = NU(y, x)$;*
- *Monotonicity: $NU(x, y) \leq NU(x, d)$, if $y \leq d$;*
- *Associativity: $NU(x, NU(y, d)) = NU(NU(x, y), d)$;*
- *Annihilator element: $\exists u \in [0, 1]$, s.t. $NU(x, u) = u$*

In the consensus model which will be proposed in the current paper, the weights of experts will be determined based on their performance in both the current round and the previous rounds during the CRP. The main purpose is to make use of historical information to provide a more comprehensive weight determination process [10]. To realize the goal, we need to apply an operator satisfying the properties: commutativity, monotonicity and associativity. Obviously, nullnorm operators can be the choice. Without loss of generality, a specific nullnorm operator in [26] is applied in the current work and presented as below.

$$NU(x, y) = \begin{cases} uS(\frac{x}{u}, \frac{y}{u}) & x, y \in [0, u]^2 \\ u + (1-u)T(\frac{x-u}{y-u}, \frac{1-y}{1-u}), & x, y \in (u, 1]^2 \\ u, & otherwise \end{cases} \tag{1}$$

where S and T are t-norm and t-conorm, product t-norm $T(x, y) = xy$ and t-conorm $S(x, y) = x + y - xy$ are adopted.

2.4 Self-management mechanisms for non-cooperative behaviors

During the CRP, some experts may exhibit non-cooperate behaviors, motivated by personal benefits, interest, or other complex factors. Effectively managing such behaviors is crucial for enhancing the efficiency and reasonable decision making [14]. A self-management mechanism is usually consisted of the following contents.

(1) *Identification of non-cooperative behaviors*
Different mechanisms for identifying non-cooperative behaviors have been proposed in the literature. These mechanisms usually categorize behaviors into two or three categories, as discused in existing studies [16, 27–30].

(2) *Weight updating of experts*
The self-management of non-cooperate behaviors is usually achieved by adjusting weights of the experts according to their performance in CRP. MMEM [16] has been used as a tool to update the weights for experts according to their non-cooperative behaviors, and to realize the self-management during the CRP in GDM [16] and LSGDM [17].

3 A consensus model dealing with non-cooperative behaviors by using a self-management weight generation scheme

In this section, to deal with non-cooperative behaviors during the CRP, a group consensus model with a self-management weight determination mechanism based on comprehensive score is proposed, as shown in Fig. 1.

3.1 CRP in GDM problem with non-cooperative behaviors

During CRP in GDM, some of the experts may seek for personal benefits rather than the group benefit, and perform non-cooperative behaviors. They may reject the manager's suggestions to achieve the group consensus, or act in a perfunctory manner. In order to speed up the CRP, it is necessary to identify non-cooperative behaviors for individuals in a reasonable manner and deal with different types of non-cooperative behaviors (such as, low professional level, over collaborate, and so on, which will be discussed in Section 4.1) in an effective way. The current work aims to propose a consensus model which deals with non-cooperative behaviors efficiently.

Let $X = \{x_1, x_2, ..., x_n\} (n \geq 2)$ be a set of alternatives, $E = \{e_1, e_2, ..., e_m\}$ be a set of experts, and $P^{(z,t)} = (p_{ij}^{(z,t)})_{n \times n}$ be the preference relations provided by expert e_z in round t. Let $W = (w^{(1,t)}, w^{(2,t)}, \ldots, w^{(m,t)})^T$ be the weighting vector, where $w^{(z,t)}$ is the weight of expert e_z in round t during the CRP, and $\hat{W} = (\hat{w}^{(1,t)}, \hat{w}^{(2,t)}, \ldots, \hat{w}^{(m,t)})^T$ be the normalized weighting vector, which satisfies that $\sum_{i=1}^{m} \hat{w}^{(i,t)} = 1$. To facilitate the understanding of this study, some frequent applied mathematical symbols that will be used in the consensus model are listed in Appendix A.1, Table 4.

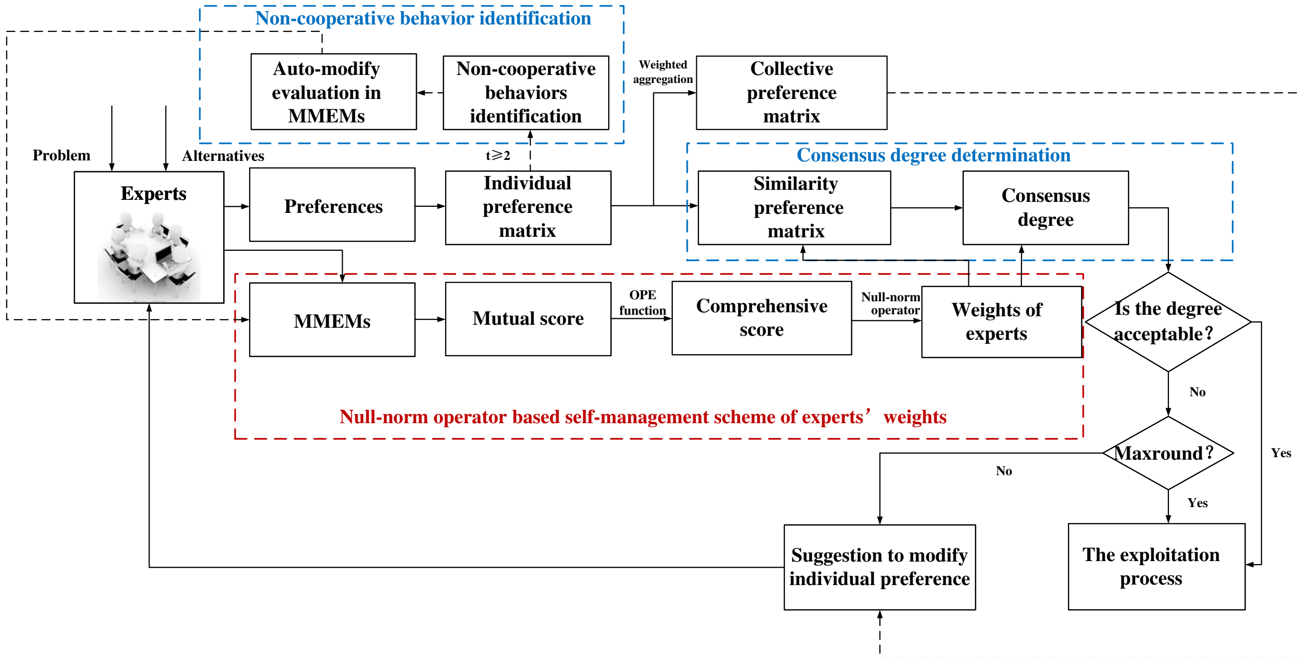

Fig. 1 Consensus model with a novel weight generation scheme

The established weight generation mechanism is integrated into the consensus model to form the framework to handle GDM problems.

(1) *Consensus degree measurement*
Following a widely applied strategy to deal with CRP in GDM, this paper applies a consensus measure based on experts' weights, to determine whether the GDM problem has reached the consensus, and whether some of the experts should adjust their preferences or not. The consensus measure proposed by Palomares et al. [31] is adapted to measure the consensus degree of the group. The similarity matrix for a pair of experts (e_z, e_h) in round t is defined by

$$SM^{(zh,t)} = (sm_{ij}^{(zh,t)})_{n\times n} \tag{2}$$

where

$$sm_{ij}^{(zh,t)} = 1 - |p_{ij}^{(z,t)} - p_{ij}^{(h,t)}| \in [0, 1] \tag{3}$$

is the similarity degree between the preferences of experts e_z and e_h on alternatives x_i over x_j in round t.
In round t, the consensus matrix $CM^t = (cm_{ij}^t)_{n\times n}$ is obtained by considering the weights of experts, where cm_{ij}^t means the consensus level of the pair of alternatives (x_i, x_j), and it is computed by

$$cm_{ij}^t = \frac{\sum_{z=1}^{m-1}\sum_{h=z+1}^{m} w_{zh}^t sm_{ij}^{(zh,t)}}{\sum_{z=1}^{m-1}\sum_{h=z+1}^{m} w_{zh}^t} \tag{4}$$

where $w^{(z,t)}$ and $w^{(h,t)} \in [0, 1]$ are the experts', e_z and e_h, weights in round t, respectively, which are determined by the mutual evaluation matrix in Section 3.2 and the null-norm operator based on self-management weight generation scheme provided in Section 3.3 and $w_{zh}^t = min(w^{(z,t)}, w^{(h,t)})$. Subsequently, the consensus level in different dimensions can be computed according to the consensus matrix as follows.

i) Consensus level of all experts on alternative x_i,

$$ca_i^t = \frac{\sum_{j=1, j\neq i}^{n} cm_{ij}^t}{n-1} \tag{5}$$

ii) Collective consensus level (group consensus level) of all experts on all alternatives,

$$cl^t = \frac{\sum_{i=1}^{n} ca_i^t}{n}, cl^t \in [0, 1] \tag{6}$$

A larger value of cl^t indicates a higher consensus level among all experts. If $cl^t = 1$, it indicates that all experts reach a full consensus. A threshold value $\overline{cl}$ is set, if $cl^t > \overline{cl}$, the consensus is reached, otherwise the preferences of all experts need to be adjusted according to the suggestions provided by the moderator, to be closer to the collective preference.

(2) Collective preference computation.
Individual preferences will be aggregated, by considering the weights of experts in round t, and the collective preference can be obtained as below.

$$p_{ij}^{(c,t)} = WA(p_{ij}^{(1,t)}, p_{ij}^{(2,t)}), \ldots, p_{ij}^{(m,t)}) = \sum_{z=1}^{m} w^{(z,t)} p_{ij}^{(z,t)} \tag{7}$$

(3) *Feedback generation*
Let the preference matrix of expert e_z in round t be $P^{(z,t)} = (p_{ij}^{(z,t)})n \times n(z = 1, 2, \ldots, m)$, and let the collective preference matrix in round t be $P^{(c,t)} = (p_{ij}^{(c,t)})n \times n$. Let the adjusted preference of $P^{(z,t)}$ in round $t+1$ be $P^{(z,t+1)} = (p_{ij}^{(z,t+1)})n \times n(z = 1, 2, \ldots, m)$, and the adjustment rule is presented as (8), which is adapted from the strategy proposed in [31].

$$\begin{cases} p_{ij}^{(z,t+1)} \in [\min(p_{ij}^{(z,t)}, p_{ij}^{(c,t)}), \max(p_{ij}^{(z,t)}, p_{ij}^{(c,t)})] & if i \le j \\ p_{ij}^{(z,t+1)} = 1 - p_{ji}^{(z,t+1)}, & if i > j \end{cases} \tag{8}$$

(4) *Non-cooperative behaviors identification*
It should be noticed that (8) is the suggestion provided by moderator to experts, however not all experts are glad to or have the ability to do adjustments according to it. That is to say, non-cooperative behaviors exist. The non-cooperative behaviors will be classified into 7 different types, which will be discussed in a detailed way in Section 4.1. To deal with these behaviors, non-cooperative behavior matrix will be established as is presented in Section 4.2, and a self-management mechanism for updating experts' weights is provided in Section 4.3.

(5) *The exploitation process*

The selection process is carried out following the strategy introduced by Herrera-Viedma et al. in [32]. Denote the collective preference relation by $P^{(c,t)} = (p_{ij}^{(c,t)})_{n\times n}$ and based on $P^{(c,t)} = (p_{ij}^{(c,t)})_{n\times n}$, the collective preference for alternative x_i is computed by

$$pr_i^{(c,t)} = OWA\left(pr_{i1}^{(c,t)}, pr_{i2}^{(c,t)}), \ldots, pr_{in}^{(c,t)}\right) \tag{9}$$

where OWA is the ordered weighted aggregation operator based on a linguistic quantifier [33, 34] to do the aggregation(see Appendix D). The alternative with the largest collective preference value will be chosen as the solution to the decision problem, it can be not unique. The collective preference vector over X can be denoted by $Pr^{(c,t)} = (pr_1^{(c,t)}, pr_2^{(c,t)}), \ldots, pr_n^{(c,t)})^T$.

3.2 Generation of experts' comprehensive scores

In this subsection, we define the comprehensive score based on the expert's multi-attribute mutual evaluation matrix (MMEMs). In the later round in CRP, the demanding for cooperation should be higher than in the previous ones. It is easy to explain, suppose that an expert always cooperates in the first rounds, and his weight keeps growing through several rounds of feedback, but in the last rounds of CRP suddenly he/she changes the attitude heavily, the harm to consensus reaching will be much more larger than the harm caused by the expert performs non-cooperative at the beginning of CRP. Our proposal for a comprehensive score that will reflect the different demanding for cooperation at different stages of CRP, i.e., the demanding the later rounds of CRP is higher. For this reason, the comprehensive score will be used to obtain experts' weights. The initial mutual evaluation score is established based on the subjective judgment of each expert regarding their peers, considering various factors such as the knowledge reserve, professional experience, history performance, etc.

Recall that $X = \{x_1, x_2, ..., x_n\}(n \ge 2)$ is a set of alternatives, $E = \{e_1, e_2, ..., e_m\}$ is a set of experts. Let $A = \{a_1, a_2, ..., a_l\}(l \ge 1)$ be a set of attributes related to non-cooperative behaviors of experts, $\lambda = \{\lambda_1, \lambda_2, ..., \lambda_l\}^T$ be the weight vector of attributes in A, each component of the weight vector represents the importance of a non-cooperate behavior during the determination process of experts' weights. In round t of the CRP, let $P^{(z,t)} = (p_{ij}^{(z,t)})_n \times_n$ $(i, j \in \{1, \cdots, n\})$ be the preference relation of expert e_z, experts are allowed to provide mutual score on each other according to attributes that are associated with non-cooperative behaviors. Based on that, let $V^{(z,t)} = (v_{ij}^{(z,t)})_m \times_l$ $(i \in \{1, \cdots, m\}, j \in \{1, \cdots, l\})$ be the MMEM provided by expert e_z , $v_{ij}^{(z,t)}$ represents the evaluation score of the expert e_i regarding the expert e_z on the attribute a_j. If the expert evaluates himself/herself, the score value is assigned as "null". According to the approach in [35], the items in the normalized MMEM $\overline{V}^{(z,t)} = (\overline{v}_{ij}^{(z,t)})_m \times_l$ can be obtained by:

i) for benefit attribute a_j, $\overline{v}_{ij}^{(z,t)} = \frac{v_{ij}^{(z,t)}}{\sum_{i=1,i\neq z}^{m} v_{ij}^{(z,t)}}$;

ii) for cost attributes a_j, $\overline{v}_{ij}^{(z,t)} = \left(\frac{1}{v_{ij}^{(z,t)}}\right) / \left(\frac{1}{\sum_{i=1,i\neq z}^{m} v_{ij}^{(z,t)}}\right) = \frac{\sum_{i=1,i\neq z}^{m} v_{ij}^{(z,t)}}{v_{ij}^{(z,t)}}$;

iii) for any attribute a_j, $\overline{v}_{ij}^{(z,t)} = null(i = z)$.

In the current work, without loss of generality, we use attributes in the MMEM according to the classification of non-cooperate behaviors in Section 4, as: cooperative attitude, reliability, cooperative ability, professional level, fairness, not over collaborate, and not conspiracy. All of them are benefit attributes, that is, the more cooperative an expert is, the larger the related value of item is in the MMEM. For the convenience of discussion, when we mention $v_{ij}^{(z,t)}$ in the following contents, it means the normalized mutual score, i.e., $\overline{v}_{ij}^{(z,t)}$.

In round t, the mutual score of expert e_z defined in [17], can be denoted by $\mu^{(z,t)}$ and computed by using the following equation.

$$\mu^{(z,t)} = \frac{1}{m-1} \sum_{i=1, i \neq z}^{m} \left(\sum_{j=1}^{l} \lambda_j v_{ij}^{(z,t)} \right) \tag{10}$$

The mutual score reflects the importance degree of expert e_z according to other experts' evaluations about non-cooperative degree. It is easy to achieve that $\mu^{(z,t)} \in [0, 1]$. Afterwards, a specific function is applied in the current work,[1] to define the comprehensive score based on mutual score.

$$\sigma_k\left(y\right) = \frac{y - y^{k \cdot n}}{(k \cdot n - 1)(1-y)} \tag{11}$$

where $k, n \in N^+$.

The comprehensive score of the expert e_z in round t is expressed as $\sigma^{(z,t)}$, which is obtained by

$$\sigma_k^{(z,t)} = \sigma_k(\mu^{(z,t)}) \in [0, 1] \tag{12}$$

The mutual score can be transformed into a comprehensive score through the OPE function σ_k(see Appendix A, Fig. 9). With a fixed consensus round n, the value of comprehensive score increases when mutual score increases. The value of mutual score is closely related to the cooperative degree of experts, there is a direct proportionality relation. That means, the more cooperative an expert is, the larger comprehensive score function. Meanwhile, with a fixed mutual score, the value of the comprehensive score decreases with the increase of the number of consensus rounds. That is to say, to achieve the same comprehensive score in the later round of CRP, the mutual score should be higher. In the later round of CRP, the expectation for cooperative degree is higher, the comprehensive score is defined to reflect this demanding. In the following sections, the application of comprehensive score contributes to achieve the goal that: for the same level non-cooperation, the punishment in the later period of CRP is greater than that in the earlier period, during the weight determination process.

Hyper-parameter k can be used to control the degree that moderator of CRP holds opinion that "non-cooperative behavior in later rounds of CRP is more harmful than such behavior in early rounds". The larger k is, the more moderator supports that "punishment on weights of experts who perform non-cooperative behaviors in later rounds should be larger than in the beginning rounds". For a fixed $n(n > 1)$, the larger k is, the larger the difference in value of $\sigma_k(y)$ with $n = 1$ and $n = n_0(n_0 > n)$. For instance, in Fig. 9 we present the OPE functions with $k = 1$ and $k = 2$, respectively. For a fixed y and a fixed n, we have $\sigma_1(y) > \sigma_2(y)$, that means for a fixed mutual score on an expert, the comprehensive score computed by (12) by σ_2 is smaller then the comprehensive score computed by σ_1. Then, the weight of this expert will also be reduced more (by the scheme introduced in Section 3.4, (13)-(16)). In the following contents, we use $k = 2$ without lost of generation, and denote OPE function with $k = 2$. i.e. σ_2 by σ for simplicity.

Experts only need to provide evaluations in MMEM once, afterwards mutual score and comprehensive score are computed by (10) and (12), respectively. From the second round of the CRP, the item in MMEM will be updated by applying (31) and (32), which will be detailed in Section 4.2, based on which the mutual score and the comprehensive score could be updated, correspondingly.

3.3 Generation of experts' weights based on comprehensive score

In the current subsection, the comprehensive score will be applied to obtain the weights for experts, and a weight dynamic iterative model will be set up to promote the achievement of consensus.

An expert's weight should not only be related to the comprehensive score in the current round, which reflects the cooperative level in that round, but also to the comprehensive score in the previous round, which reflects the historical cooperative level. By applying the nullnorm operator denoted by NU, the cooperation behavior in the previous round can be further concerned to determine the weights, to take use of the information in a more comprehensive way. Considering the information collected in the current round and the previous

[1] Considering that if $k = 1$, function σ_k has ever been applied to describe the relationship between the orness of the pessimistic exponential OWA operator[36, 37], we call σ_k the orness pessimistic exponential(OPE) function (see Fig. 9) in the current work. The reason why we choose OPE function is that: supposed that k is fixed, i) for a fixed y, the value of σ_k (y) decreases as value n increases, ii) for a fixed n, the value of σ_k (y) increases as value y increases. Taking use of these two properties, we can realize the distinguished treatment for non-cooperative behaviors in different periods of CRP by applying (12).

one, we have

$$w^{(z,t)} = \begin{cases} \sigma^{(z,t)}, & t = 1 \\ NU\left(\sigma^{(z,t)}, \sigma^{(z,t-1)}\right), & t \geq 2 \end{cases} \quad (13)$$

$w^{(z,t)}$ represents the weight of expert e_z in round t, it can be computed from the comprehensive score $\sigma^{(z,t)}$ in round t and the score $\sigma^{(z,t-1)}$ in the previous round $t-1$. Equation (13) establishes a link between the comprehensive score of experts and their weights. In the current round of CRP, if an expert is more cooperative than in the previous one, then his/her comprehensive score is higher, and then the weight should be increased; If an expert is less cooperative than in previous round, the expert's comprehensive score should be lower, and then the weight should be reduced. If in the previous round an expert was cooperative, implies a high comprehensive score as well as a high value of weight, then his/her weight in the current round should be kept or increased; If an expert was uncooperative, implies a low comprehensive score as well as a low value of weight, then the expert's weight in the current round should be reduced. In this way, during the weight determination process, not only the comprehensive score in the current round could be considered, but also the comprehensive score reflected by the weight in the previous round could be taken into consideration. The application of nullnorm operator can help us achieve the purpose of controlling the impacts of non-cooperative behaviors of experts.

If the information collected in the current round and previous two consecutive rounds (i.e., 3 rounds in all) are considered by the moderator, (13) can be further developed as

$$w^{(z,t)} = \begin{cases} \sigma^{(z,t)}, & t = 1 \\ NU\left(\sigma^{(z,t)}, \sigma^{(z,t-1)}\right), & 3 \geq t \geq 2 \\ NU\left(\left(\sigma^{(z,t)}, \sigma^{(z,t-1)}\right), \sigma^{(z,t-2)}\right) & t \geq 3 \end{cases} \quad (14)$$

The commutativity, monotonicity and associativity property of nullnorm operator ensures that i) if one of the element increases, the computation result increases; ii) the value of $\sigma^{(z,t)}$, $\sigma^{(z,t-1)}$ and $\sigma^{(z,t-2)}$ has the same impact on the computation result. If more rounds of information (such as η rounds) need to be considered, it is suggested that

$$w^{(z,t)} = \begin{cases} \sigma^{(z,t)}, & t = 1 \\ NU\left(\sigma^{(z,t)}, \sigma^{(z,t-1)}\right), & 3 \geq t \geq 2 \\ \cdots & \cdots \\ NU\left(NU\left(\cdots NU\left(\left(\sigma^{(z,t)}, \sigma^{(z,t-1)}\right), \sigma^{(z,t-2)}\right)\cdots\right), \sigma^{(z,t-\eta+1)}\right) & t \geq \eta \end{cases} \quad (15)$$

Here, the associativity property of the nullnorm operator ensures that the value of comprehensive score in each has the same impact on the computation result.

The weight $w^{(z,t)}$ should be normalized at this stage, and denoted by $\hat{w}^{(z,t)}$.

$$\hat{w}^{(z,t)} = \frac{w^{(z,t)}}{\sum_{i=1}^{m} w^{(z,t)}} \quad (16)$$

The normalized weights will be applied in the preferences aggregation process and the consensus degree calculation

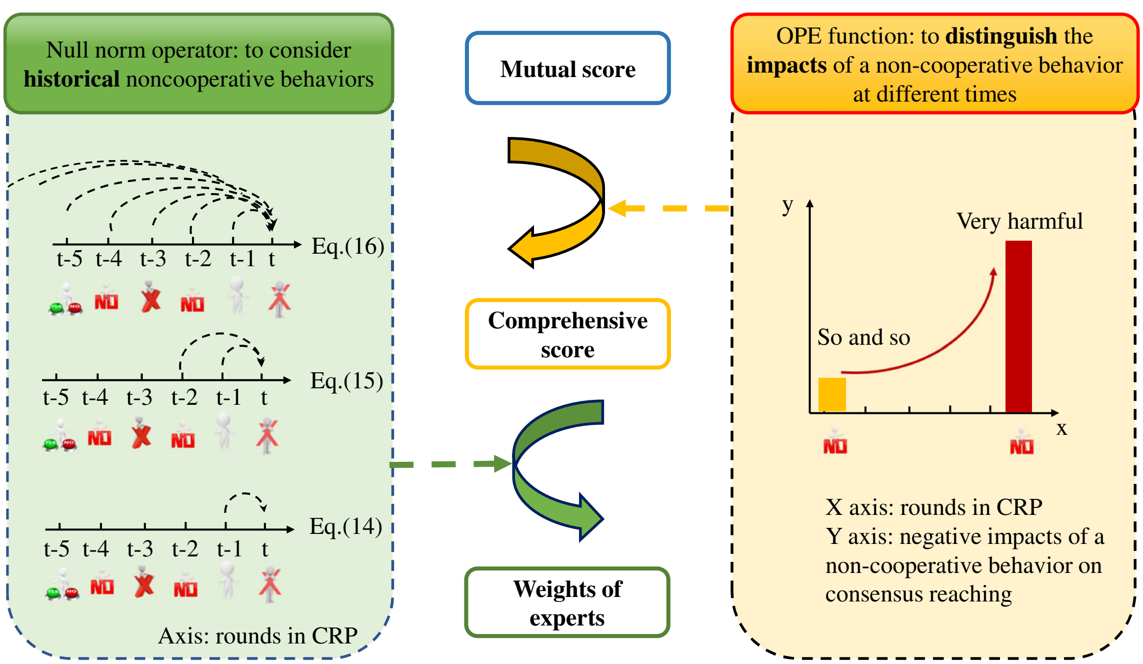

Fig. 2 Mechanism for establishing the weights of experts

process. Figure 2 indicates the application of OPE function and null-norm operator in determining weights of experts in a intuitive way.

4 Management of non-cooperative behaviors and its effects in CRP

We have previously mentioned that in specialized literature non-cooperative behaviors are similar managed in spite of such behaviors may come from different reasons. In this section, seven experts' non-cooperative behaviors during the CRP are identified according to the nature of the behavior. Hence, different penalty coefficients are designed, to effectively manage different types of the non-cooperative behaviors see Fig. 3.

4.1 Non-cooperative behaviors identification

From the second round of the CRP, preference could be provided by experts considering the feedback information, therefore, in the following discussion to identify seven types

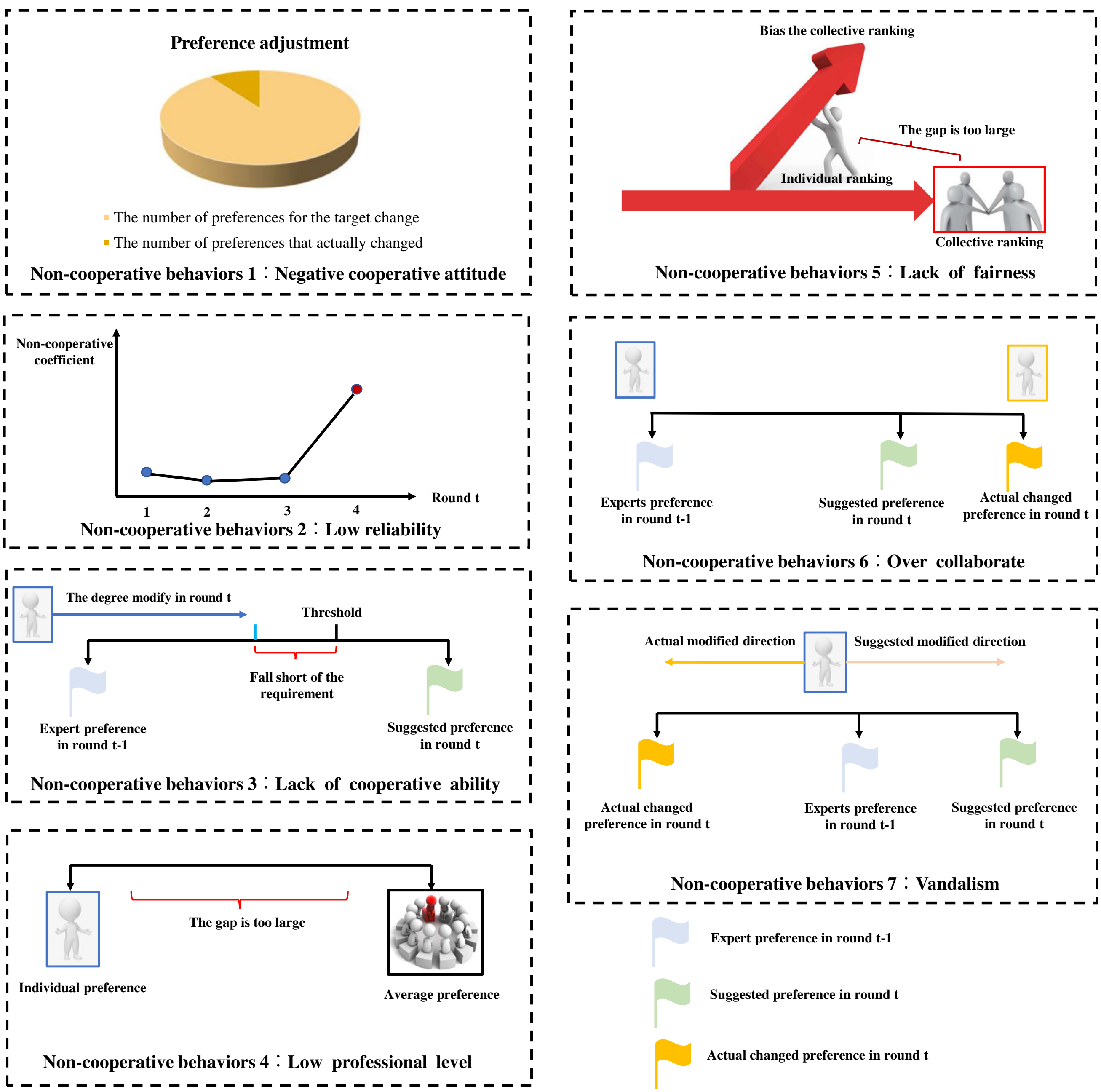

Fig. 3 The seven types of non-cooperative behavior of experts defined in this study

of non-cooperative behaviors, we assume that the round $t \geq 2$ [16].

(1) *Non-cooperative behavior a_1: negative cooperative attitude*
During the CRP, if experts are requested to modify their preferences to pursue a consensus, but the experts choose not to modify their preferences at all, the behavior is called non-cooperative behavior 1, which can be defined by introducing the cooperation coefficient. Let $\#ADV^{(z,t)}$ be the number of preferences that the expert e_z is advised to modify in round t. $\#ACP^{(z,t)}$ is the number of preferences that the expert accepts to change, that is, the expert modifies his/her preferences according to the feedback process in round $t (t \geq 2)$ during the CRP. The cooperation coefficient of experts in round $t (t \geq 2)$ is denoted by $CC^{(z,t)}$ and defined by (17).

$$CC^{(z,t)} = \begin{cases} 1, & \#ADV^{(z,t)} = 0 \\ \frac{\#ACP^{(z,t)}}{\#ADV^{(z,t)}}, & else \end{cases} \tag{17}$$

Correspondingly, the coefficient of noncooperation is denoted by $NC(a_1)^{(z,t)}$ and defined by

$$NC(a_1)^{(z,t)} = 1 - CC^{(z,t)} \tag{18}$$

The higher the value of non-cooperation coefficient $NC(a_1)^{(z,t)}$, the less cooperative the expert's e_z behavior is in round $t(t \geq 2)$. Let $\delta(a_1)$ ($\delta(a_1) \in (0, 1)$) be an pre-established threshold. If $NC(a_1)^{(z,t)} > \delta(a_1)$, we call that the expert e_z performs non-cooperative behavior a_1 in round $t(t \geq 2)$.

(2) *Non-cooperative behavior a_2: low reliability*
The experts' non-cooperation coefficient may change during the CRP. In a healthy CRP scheme, the non-cooperative behavior of most experts are expected to be lower and lower with the increase of the number of rounds. However, it is possible that the non-cooperation coefficient of some experts may increase abruptly in a certain round, although he/she keeps performing cooperative in previous several rounds. Such a behavior is conspiratorial unco-ordination, the expert is identified as a conspirator/schemer, who aims to slow down consensus.
The non-cooperation coefficient of expert e_z in round t related to a_2 is denoted by $NC(a_2)^{(z,t)}$ and defined by (19).

$$NC(a_2)^{(z,t)} = NC(a_1)^{(z,t)} - \frac{\sum_{i=1}^{t-1} NC(a_1)^{(z,i)}}{t-1} \tag{19}$$

The higher of non-cooperation coefficient $NC(a_2)^{(z,t)}$, the more conspiratorial the expert e_z is in round t. Let $\delta(a_2)$ ($\delta(a_2) \in (0, 1)$) be an pre-established threshold. If $NC(a_2)^{(z,t)} > \delta(a_2)$, we call the expert e_z in round $t(t \geq 2)$ performs non-cooperative behavior a_2.

(3) *Non-cooperative behavior a_3: lack of cooperative ability*
If some experts receive feedback to do modifications, they would like to cooperate but only a little bit, and the modification result is still too far form the suggestion, the behavior will also lead to difficulty for the group to reach consensus. This kind of behavior is classified into non-cooperative behavior 3.
Suppose that the preference matrix provided by expert e_z in round t is $P^{(z,t)} = (p_{ij}^{(z,t)})_{n \times n}$, where $p_{ij}^{(z,t)}$ is the preference of expert e_z in round t, corresponding to the item on position row i, column j in the matrix. Let $p_{ij}^{(c,t)}$ be the collective preference of all experts in round t, corresponding to the item on position row i, column j, which is also the target that expert e_z is advised to modify to in round t.
Let

$$D^{(z,t)} = \sum_{i=1}^{n} \sum_{j=1}^{n} |p_{ij}^{(z,t)} - p_{ij}^{(z,t-1)}| \tag{20}$$

and

$$D_c^{(z,t)} = \sum_{i=1}^{n} \sum_{j=1}^{n} |p_{ij}^{(c,t-1)} - p_{ij}^{(z,t-1)}| \tag{21}$$

where $D^{(z,t)}$ represents the adjustment amount of expert e_z's preference in round t, $D_c^{(z,t)}$ represents the recommended amount of modifications for expert e_z in round t.
Let the coefficient

$$NC(a_3)^{(z,t)} = 1 - \frac{D^{(z,t)}}{D_c^{(z,t)}} \tag{22}$$

where $\frac{D^{(z,t)}}{D_c^{(z,t)}}$ represents the ratio of the expert e_z's practical adjustment to the recommended adjustment. If $D_c^{(z,t)} = 0$, set $NC(a_3)^{(z,t)} = 0$. The higher the value $NC(a_3)^{(z,t)}$, the greater the degree to which the expert failed to adjust as recommended in round t. Let $\delta(a_3)$ ($\delta(a_3) \in (0, 1)$) be an pre-established threshold. If $NC(a_3)^{(z,t)} > \delta(a_3)$, the behavior of expert e_z in round t is non-cooperative behavior a_3.

(4) *Non-cooperative behavior a_4: low professional level*
If there is an expert whose preferences are always significantly different from those of other experts, we infer that this expert has major problems in professional competence and his/her opinion may generate serious errors in the final results. The preferences of individuals and

the average preferences will be compared. Let $p_{ij}^{(a,t)}$ be the preference obtained by computing the average of the group preferences, as is shown by (23).
Let

$$p_{ij}^{(a,t)} = \frac{1}{m}\sum_{z=1}^{m} p_{ij}^{(z,t)} \tag{23}$$

where $p_{ij}^{(z,t)}$ is e_z respect to the preferences of x_i and x_j in round t, then $p_{ij}^{(a,t)}$ is the average preference about x_i to x_j in round t.
And the distance from the preference of expert e_z and the average opinion can be reflected by coefficient $NC(a_4)^{(z,t)}$ and computed by

$$NC(a_4)^{(z,t)} = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{j=1}^{n}|p_{ij}^{(z,t)} - p_{ij}^{(a,t)}| \tag{24}$$

Let $\delta(a_4)$ ($\delta(a_4) \in (0,1)$) be a pre-established threshold. If $NC(a_4)^{(z,t)} > \delta(a_4)$, we call the behavior of expert e_z in round t is non-cooperative behavior a_4.

(5) *Non-cooperative behavior a_5: lack of fairness*
Some experts may hide their true preferences during the CRP in GDM, and intend to profit from it. For example, an expert may reduce the priority of an alternative deliberately elevating the ranking of other alternatives. This behavior will not only reduce the efficiency of consensus, but also leads to biased decision making results. Dong et al. [17] figured out this type of non-cooperative behavior, and in this proposal we view it as non-cooperative behavior a_5.
Let $Pr^{(c,t-1)} = (pr_1^{(c,t-1)}, pr_2^{(c,t-1)}, ..., pr_n^{(c,t-1)})^T$ be the preference vector obtained from the collective assessments of the group in round $t-1$, in which OWA operator is applied to do the aggregation, and $Pr^{(z,t)} = (pr_1^{(z,t)}, pr_2^{(z,t)}, ..., pr_n^{(z,t)})^T$ be the preference vector obtained from the expert e_z in round t, which is also based on the OWA operator.
Let

$$O^{(z,t)} = (o^{(z,t)}(x_1), o_2^{(z,t)}(x_2), ..., o^{(z,t)}(x_n))^T \tag{25}$$

be the ranking vector obtained from the preference of expert e_z, where $o^{(z,t)}(x_i)$ is the position of the alternative x_i in X according to $Pr^{(z,t)}$. For example, if $Pr^{(z,t)} = (0.2, 0.6, 0.4)^T$, we have $O^{(z,t)} = (3, 1, 2)^T$. Besides, $O^{(c,t)} = (o^{(c,t)}(x_1), o_2^{(c,t)}(x_2), ..., o^{(c,t)}(x_n))^T$ is the ranking vector obtained from the collective preference.
By applying a pre-established threshold $\delta(a_5)(\delta(a_5) \in (0,1))$, a coefficient $NC(a_5)^{(z,t)}$ is defined as below.

$$NC(a_5)^{(z,t)} = \begin{cases} 1, \ if|o^{(z,t)}(x_o) - o^{(c,t-1)}(x_o)| > round(\delta(a_5)\times n) \\ 0, \ else \end{cases} \tag{26}$$

where $round$ is a round operator, and $o^{(z,t)}(x_o)$ is the rank value of $x_o(x_o \in [x_1, \cdots, x_n])$, where x_0 satisfies the condition that $o^{(c,t-1)}(x_o) = 1$. The coefficient $NC(a_5)^{(z,t)}$ is computed by considering the alternative ranks first based on the collective preference.
For example, suppose that $Pr^{(1,t)} = (0.2, 0.6, 0.4)^T$ and $Pr^{(c,t-1)} = (0.5, 0.2, 0.4)^T$. Based on $Pr^{(c,t-1)}$, we have $o^{(c,t-1)}(x_o) = o^{(c,t-1)}(x_1) = 1$. According to (25), we can obtain $o^{(1,t)} = (3, 1, 2)^T$ and $o^{(c,t-1)} = (1, 3, 2)^T$, so $o^{(1,t)}(x_1) = 3$, we set $\delta(a_5) = 0.4$, from $|3-1| > round(1.2)$, we get $NC(a_5)^{(1,t)} = 1$, then we know that expert e_1 performs non-cooperative behavior a_5 in round t.

(6) *Non-cooperative behavior a_6: over collaborate*
Let us recall (8), under normal circumstance, the adjustment rule is presented as

$$\begin{cases} p_{ij}^{(z,t)} \in [min(p_{ij}^{(z,t-1)}, p_{ij}^{(c,t-1)}), max(p_{ij}^{(z,t-1)}, p_{ij}^{(c,t-1)})], & if \ i \le j \\ p_{ij}^{(z,t)} = 1 - p_{ji}^{(z,t)}, & if \ i > j \end{cases} \tag{27}$$

Suppose that in round t of CRP, the preference of e_z over (x_i, x_j) is suggested to be modified from $p_{ij}^{(z,t-1)}$ to $p_{ij}^{(c,t-1)}$, however if the expert e_z's modification goes beyond the interval $[\min(p_{ij}^{(z,t-1)}, p_{ij}^{(c,t-1)})$, $\max(p_{ij}^{(z,t-1)}, p_{ij}^{(c,t-1)})]$ in practice, that is, expert does over modification, this type of behavior is viewed as a type of non-cooperative behavior which is caused by over collaboration.
A coefficient $NC(a_6)^{(z,t)}$ is defined as below.

$$NC(a_6)^{(z,t)} = \begin{cases} 1, \ if p_{ij}^{(z,t-1)} < p_{ij}^{(c,t-1)} < p_{ij}^{(z,t)} \ or \ p_{ij}^{(z,t)} < p_{ij}^{(c,t-1)} < p_{ij}^{(z,t-1)}, \#(p_{ij}^{(z,t)}) \ge \frac{1}{2}n^2 \\ 0, \ else \end{cases} \tag{28}$$

Here, $\#(p_{ij}^{(z,t)})$ is the number of items in the preference relation of e_z in round t, and (28) indicates that if more than half of the preference values of an expert satisfies $p_{ij}^{(z,t-1)} < p_{ij}^{(c,t-1)} < p_{ij}^{(z,t)}$ or $p_{ij}^{(z,t)} < p_{ij}^{(c,t-1)} < p_{ij}^{(z,t-1)}$, then this expert is identified performing behavior a_6. That is, if $NC(a_6)^{(z,t)} = 1$, we call the behavior of expert e_z in this round t is non-cooperative behavior a_6.

(7) *Non-cooperative behavior a_7: conspiracy*
Let us recall (27), suppose that in round t of CRP, the preference of e_z over (x_i, x_j) is suggested to be modified from $p_{ij}^{(z,t-1)}$ to $p_{ij}^{(c,t-1)}$, however the expert goes into the opposite direction to the suggested one, this type of behavior is viewed as a type of non-cooperative behavior which is related to conspiracy. This behavior has been pointed out in our previous research [38, 39], it is modeled as below.

A coefficient $NC(a_7)^{(z,t)}$ is defined as below.

$$NC(a_7)^{(z,t)} = \begin{cases} 1, \; if \; p_{ij}^{(z,t-1)} < p_{ij}^{(c,t-1)} \; and \; p_{ij}^{(z,t)} < p_{ij}^{(z,t-1)} \; or \\ \quad if \; p_{ij}^{(z,t-1)} < p_{ij}^{(z,t)} \; and \; p_{ij}^{(c,t-1)} < p_{ij}^{(z,t-1)} \; \#(p_{ij}^{(z,t)}) \geq \frac{1}{3}n^2 \\ 0, \; else. \end{cases} \tag{29}$$

This equation indicates that if more than one thrid of the preference valus of an expert satisfies $p_{ij}^{(z,t-1)} < p_{ij}^{(c,t-1)}$ and $p_{ij}^{(z,t)} < p_{ij}^{(z,t-1)}$, or satisfies $p_{ij}^{(z,t-1)} < p_{ij}^{(z,t)}$ and $p_{ij}^{(c,t-1)} < p_{ij}^{(z,t-1)}$, that is, $NC(a_7)^{(z,t)} = 1$, we call the behavior of expert e_z in this round t is non-cooperative behavior a_7.

Seven types of non-cooperative behaviors have been introduced. Besides, during the CRP process in a real decision making problem, sometimes not all types of behaviors are necessary to be considered. Without loss of generality, the attributes set corresponding to non-cooperate behaviors are denoted by $A = \{a_1, a_2, \ldots, a_l\}$. A non-cooperative behavior matrix $NC^{(t)} = (r_{zf})_{m \times l}$ in round t during CRP is established to describe the performance of experts $\{e_1, e_2, \ldots, e_m\}$ in different behaviors, in which $r_{zf} = 1$ if the expert e_z performs non-cooperative behavior a_f, and $r_{zf} = 0$ indicates that the expert e_z does not perform non-cooperative behavior a_f.

$$NC^{(t)} = \begin{pmatrix} r_{11} & r_{12} & \ldots & r_{1q} \\ r_{21} & r_{22} & \ldots & r_{2q} \\ \ldots & \ldots & \ldots & \ldots \\ \ldots & \ldots & \ldots & \ldots \\ r_{m1} & r_{m2} & \ldots & r_{mq} \end{pmatrix} \tag{30}$$

4.2 The adjustment mechanism of MMEM for dealing with non-cooperative behavior

In a practical GDM problem, it is hard to predict what kind of non-cooperative behavior experts will perform, so in each round of CRP it is necessary to distinguish the behavior of experts first, and then deal with different behaviors accordingly. By introducing a self management mechanism to control the weights of attribute to do preferences aggregation during the CRP, the non-cooperative behavior of experts can be well addressed.

Table 1 Penalize factors for different non-cooperative behaviors

Attributes	a_1	a_2	a_3	...	a_l
Penalize factor	$\theta(a_1)$	$\theta(a_2)$	$\theta(a_3)$	...	$\theta(a_l)$

In this proposal, the attributes in the MMEM are listed as follows: Cooperative Attitude(a_1), Reliability(a_2), Cooperative Ability(a_3), Fairness(a_4), Professional level(a_5), Not over collaborate (a_6), and Not conspiracy (a_7). Each attribute corresponds to a kind of non-cooperative behavior which is mentioned in Section 4.1, and each non-cooperative behavior corresponds to a penalty factor. Once the expert is identified performing a non-cooperative behavior, the evaluation value in the MMEM with the corresponding attribute will be adjusted by applying the following strategy. The adjusted MMEM is then applied to update the weights of experts during the CRP.

Let θ be the penalize factor function, which can be viewed as a fuzzy set defined on the universe of attributes $\{a_1, a_2, \cdots, a_l\}$, as is shown by Table 1.

In the current work, $l = 7$. If an expert e_z is identified performing a non-cooperative behavior $a_1 - a_4$ $j (j \in \{1, \cdots, 4\})$, the evaluation on this expert regarding to the attribute a_j is modified by

$$v_{ij}^{(z,t+1)} = \begin{cases} null, & if \quad i = z \\ v_{ij}^{(z,t)} \times (1 - \theta(a_j)), & if \quad i \neq z \text{ and } NC(a_j)^{(z,t)} \geq \delta(a_j) \\ v_{ij}^{(z,t)}, & if \quad i \neq z \text{ and } NC(a_j)^{(z,t)} < \delta(a_j) \end{cases} \tag{31}$$

If an expert is identified as performing a non-cooperative behavior $a_5 - a_7$ $j (j \in \{5, 6, 7\})$, the evaluation on this expert should be decreased by

$$v_{ij}^{(z,t+1)} = \begin{cases} null, & if \quad i = z \\ v_{ij}^{(z,t)} \times (1 - \theta(a_j)), & if \quad i \neq z \text{ and } NC(a_j)^{(z,t)} = 1 \\ v_{ij}^{(z,t)}, & if \quad i \neq z \text{ and } NC(a_j)^{(z,t)} = 0 \end{cases} \tag{32}$$

4.3 Effect of different non-cooperative behaviors on the weight generation scheme in CRP

The mechanism established in this study is mainly used to regulate seven different kinds of non-cooperative behaviors

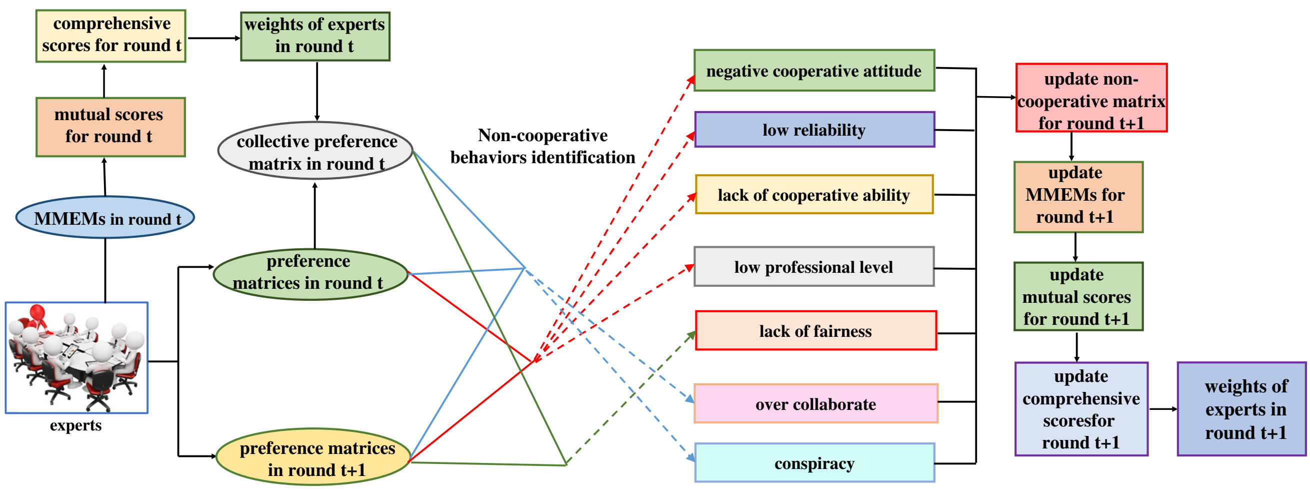

Fig. 4 Mechanism to update experts' weights based on non-cooperative behaviors in CRP

of experts in the consensus process, so as to promote consensus results faster and more efficient. The non-cooperative behaviors identification basis and the weights updating scheme is shown by Fig. 4. For instance, the behavior "lack of fairness" of an expert in round $t + 1$ is identified based on the collective preference in round t and his/her preference in in round $t + 1$. The main process of the mechanism is summarized as follows: (1) Calculate the consensus degree of the group in the first round of CRP, based on the initial preference matrix and MMEMs provided by experts; (2) From the second round of the CRP, evaluate that whether some of the experts perform non-cooperative behaviors, according to the preference modification of experts. Furthermore, determine which type of non-cooperative behavior each non-cooperative expert belongs to; (3) If an expert performs non-cooperative behavior, the expert's score on the attribute corresponding to the MMEM will be reduced by the established mechanism introduced in Section 4.2; (4) Through the weight generation mechanism based on comprehensive score introduced in Sections 3.2 and 3.3, the weights of experts will be updated in the next round of CRP, experts who perform non-cooperative behaviors will be reduced, therefore the consensus can be reached faster.

4.4 Comparative analysis

This subsection presents a comparative analysis among the current proposal and some existing non-cooperate behavior management schemes. The comparison has been carried out from aspects of non-cooperative behavior identification mechanisms, punishment strategies for different types of non-cooperative behaviors, and experts' weights determination strategies, as is shown by Table 2.

1. Non-cooperative behavior identification. Although the non-cooperative behaviors identified in existing researches can describe the problems that may occur during the decision making, they are not comprehensive enough. Considering the following issues: (1) whether there is non-cooperative behavior reflected by the number or proportion of experts' modified preferences; (2) whether experts have unexpected preference adjustment abnormalities. The current paper identifies seven possible non-cooperative behaviors during the CRP, so as to facilitate non-cooperative behaviors management and control.
2. Determination of expert weight. Dong et al. [16] initiated application of MMEMs to obtain the weight of experts in the consensus process, and this paper made innovations on the basis of it. (1) Through the application of OPE function, the mutual score of experts are processed, so as to achieve the result that if the experts perform the same non-cooperative behavior, the punishment in the later period is greater than in the earlier period. (2) This proposal also takes the historical evaluation of experts into consideration when determining the weight of experts by using the null-norm operator, which further facilitates different treatments of experts' non-cooperative behaviors at different periods.
3. In most existing approaches in literature, the same punishment strategy are taken to deal with different kinds of non-cooperative behaviors. However, it is more convincing that different non-cooperative behaviors may have different impacts on the decision results. Therefore, the current proposal distinguishes the punishment factors of non-cooperative behaviors according to their effects, so as to achieve more reliable decision result.

Table 2 Comparison with existing GDM approaches dealing with non-cooperative behaviors

Method	Non-cooperative behavior identification	Weight determination	Strategy
Quesada et al. [40]	One type: If the ratio of the number of changed preference exceeds a threshold, the expert is judged to be non-cooperative	It is determined by the degree of collaboration, based on uninorm operator	The same update manner
Xu et al. [41]	One type: Non-cooperative behavior of experts determine the weights.	The level of cooperation and confidence is determined by the adjustment quantity proportion according to the cluster result.	Update weights through the same manner.
Xu et al. [42]	One type: The established distance formula is applied to identify non-cooperative experts	The expert weight is equalized	Update "adjust coefficient" through the same manner.
Mandal Prasenjit and Madhumangal [43]	One type: The group consensus index was used to determine whether the expert was non-cooperative	It is determined based on the number of experts in the cluster	Update weights through the same manner.
Xiang [44]	One type: It is determined by the consistency of intra-group and inter-group opinions	It is determined by Q-learning algorithm	Update weights through the same manner.
Xu et al. [45]	One type: Randomly generate the coefficient of non-cooperation	Randomly generated according to a normal distribution	Update weights through the same manner.
Li et al. [46]	One type: Random, illogical preference relation	It is determined by the consistency index	Consistency driven
Xu et al. [27]	Two types: (1) General non-cooperative behaviors (2) Serious non-cooperative behaviors	Based on point centrality and personal proximity centrality.	Update non-collaborate coefficient through the same manner
Dong et al. [16]	Three types: (1) According to the modification degree (2) According to the cooperation degree (3) According to professional technology	The weight is obtained through the mutual evaluation matrix.	Update weights through the same manner
Gou et al. [28]	Three types: (1) According to the modification degree (2) According to adjustment direction (3) According to cooperation degree	The expert weights are obtained by combining the group cluster result and the mutual evaluation matrix.	Update weights through the same manner.
Shi et al. [29]	Three types: (1) Cooperative leadership behavior (2)Non-Cooperative leadership behaviors (3) Ordinary behaviors	It is determined by the degree of collaboration, based on uninorm operator	Update weights through the same manner.
Xiong et al. [30]	Three types: (1) According to the modification degree (2) According to the difference between sub-groups and large group (3) According to cooperation degree	The expert weights are obtained by the group cluster result	Update weights through the same manner.
The current proposal	Seven types: Determined by different attributes.	Weights are updated based on comprehensive evaluation score.	Different types of behavior are dealt in different manner determined by a function.

5 CRP algorithm

This section presents the CRP algorithm with proposed the non-cooperative behaviors identification and management scheme.

Algorithm 1

Input: The preference relations $P^{(z,t)} = (p_{ij}^{(z,t)})_{n\times n}$, the MMEMs $V^{(z,t)} = (v_{ij}^{(z,t)})_{m\times l}$, the weights $\lambda = \{\lambda_1, \lambda_2, ..., \lambda_l\}^T$ for attributes related to non-cooperative behaviors of experts, the pre-established consensus threshold $\overline{cl}$, and the maximum number of rounds $t_{max} \geq 1$.
Output: The adjusted preference relations $P^{(z,t+1)} = (p_{ij}^{(z,t+1)})_{n\times n}$, the adjusted MMEMs $V^{(z,t+1)} = (v_{ij}^{(z,t+1)})_{m\times l}$, the number of iterations t.
Step 1. Let $t = 0$, $P^{(z,t)} = P^{(z,0)}$, $V^{(z,t)} = V^{(z,0)}$, $z = 1, 2, \ldots, m$;
Step 2. By (10), compute the mutual score of each expert e_z in round t as $\mu^{(z,t)} = \frac{1}{m-1}\sum_{i=1,i\neq z}^{m}(\sum_{j=1}^{l}\lambda_j v_{ij}^{(z,t)})$;
Step 3. By (12), compute the comprehensive score of each expert e_z in round t as $\sigma_k^{(z,t)} = \sigma_k(\mu^{(z,t)}) \in [0, 1]$;
Step 4. By (13), compute the weight of each expert e_z in round t as $w^{(z,t)} = \begin{cases} \sigma^{(z,t)}, & t = 1 \\ NU\left(\sigma^{(z,t)}, \sigma^{(z,t-1)}\right), & t \geq 2 \end{cases}$;
Step 5. Apply (6) to obtain the consensus degree of this round cl^t, if $cl^t \geq \overline{cl}$ or $t \geq t_{max}$, go to *Step 8*; otherwise, continue with the next step;
Step 6. By (7), compute the collective preferences $p_{ij}^{c,t}$, and then use (8) to adjust experts' preferences in round $t+1$ as $P^{(z,t+1)} = (p_{ij}^{(z,t+1)})_{n\times n}$;
Step 7. Update MMEM of expert $e_z (z = 1, 2, \ldots, m)$, $V^{(z,t+1)} = (v_{ij}^{(z,t+1)})_{m\times l}$ based on (31) and (32), according to the performances identified by (18)-(29); Let $t = t + 1$, then go back to *Step 2*;
Step 8. Output the adjusted preference relations $P^{(z,t^*+1)} = (p_{ij}^{(z,t^*+1)})_{n\times n}$ which make the consensus degree reaches the pre-set threshold $\overline{cl}$, and the adjusted MMEMs $V^{(z,t^*+1)} = (v_{ij}^{(z,t^*+1)})_{m\times l}$, here the number of iterations is t^*.

6 Case study

In this section, a real life GDM problem is presented and handled by applying the proposed model.

6.1 GDM problem formulation

The rapid spread of COVID-19 in 2019 has brought unprecedented challenges to the fresh market. Due to the increasing convenience of electronic payment in China, community group e-purchasing has become the main form of selling fresh products, and the scope of community group purchasing are gradually expanded. With the increasing challenge in the fresh e-commerce supply chain, the high loss rate and relative low logistic distribution efficiency of fresh produces transportation has been attracted people's attention. The choice of a suitable fresh distribution enterprise for a specific product becomes more significant for a seller company which chooses group purchasing as its main model of operation. Suppose that a company needs to make a choice among fresh distribution enterprises, eight experts in the field of logistics and supply chain are invited to take part into the decision on the choice of logistics distributor. After preliminary discussion, six fresh distribution enterprises stand out. In this case, the main purpose is to choose the best one from the six enterprises. Experts in $E = \{e_1, e_2, ..., e_8\}$, try to reach an agreement about the selection from fresh logistics cooperation alternatives $X = \{x_1 = \text{Zhengming}, x_2 = \text{SF Express}, x_3 = \text{Suning}, x_4 = \text{JD Express}, x_5 = \text{Rokin}, x_6 = \text{Xiahui}\}$, as shown in Fig. 5. Based on experts' judgement, among the seven non-cooperative behaviors which are declared in Section 4, non-cooperative behaviors a_1, a_2, a_3, a_4, a_5, a_6 and a_7 may

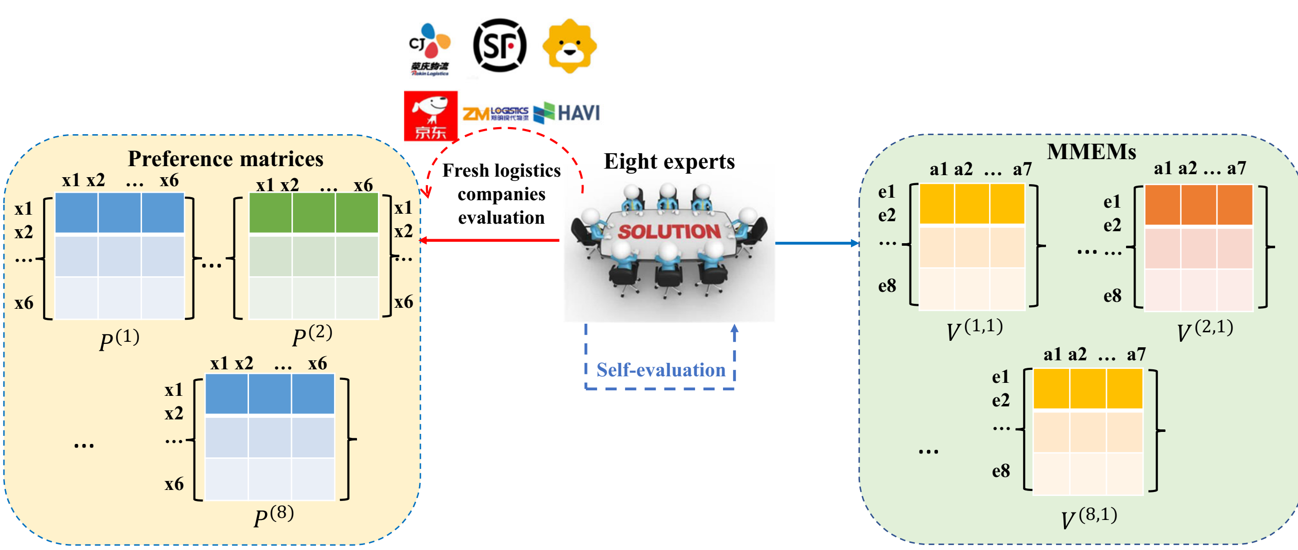

Fig. 5 The initial information provided by experts in fresh products community selection

Table 3 Penalize factor for seven types of non-cooperative behaviors

Penalize factor	$\theta(a_1)^*$	$\theta(a_2)^*$	$\theta(a_3)^*$	$\theta(a_4)^*$	$\theta(a_5)^*$	$\theta(a_6)^*$	$\theta(a_7)^*$
-	0.3	0.35	0.25	0.2	0.2	0.15	0.1

turn out to be on the consensus reaching in the current case, so it is set that $\theta(a_1)^*$ -$\theta(a_7)^*$ with values as is shown by Table 3. In this case, $\delta_{1-7} = 0.18, 1, 0.8, 0.93, 0.35, 0.5, 0.33$, $\overline{cl} = 0.85$.

6.2 The solving process

At the beginning, preference relations are requested to be provided by experts $E = \{e_1, e_2, ..., e_8\}$, and are listed as below. $P^{(i)}$ denotes the initial preference relation provided by expert e_i.

$$P^{(1)} = \begin{pmatrix} 0.5 & 0.6 & 0.7 & 0.8 & 0.4 & 0.9 \\ 0.4 & 0.5 & 0.8 & 0.6 & 0.9 & 0.7 \\ 0.3 & 0.2 & 0.5 & 0.6 & 0.7 & 0.8 \\ 0.2 & 04 & 0.4 & 0.5 & 0.4 & 0.3 \\ 0.6 & 0.1 & 0.3 & 0.6 & 0.5 & 0.7 \\ 0.1 & 0.3 & 0.2 & 0.7 & 0.3 & 0.5 \end{pmatrix}$$

$$P^{(2)} = \begin{pmatrix} 0.5 & 0.7 & 0.8 & 0.6 & 0.4 & 1 \\ 0.3 & 0.5 & 0.7 & 0.4 & 0.8 & 0.6 \\ 0.2 & 0.3 & 0.5 & 0.7 & 0.3 & 0.6 \\ 0.4 & 0.6 & 0.3 & 0.5 & 0.8 & 0.9 \\ 0.6 & 0.2 & 0.7 & 0.2 & 0.5 & 0.3 \\ 0 & 0.4 & 0.4 & 0.1 & 0.7 & 0.5 \end{pmatrix}$$

$$P^{(3)} = \begin{pmatrix} 0.5 & 0.59 & 0.22 & 0.3 & 0.46 & 0.9 \\ 0.41 & 0.5 & 0.14 & 0.25 & 0.17 & 0.8 \\ 0.78 & 0.86 & 0.5 & 0.73 & 0.7 & 0.95 \\ 0.7 & 0.75 & 0.27 & 0.5 & 0.73 & 0.93 \\ 0.54 & 0.83 & 0.3 & 0.27 & 0.5 & 0.98 \\ 0.1 & 0.2 & 0.05 & 0.07 & 0.02 & 0.5 \end{pmatrix}$$

$$P^{(4)} = \begin{pmatrix} 0.5 & 0.3 & 0.46 & 0.73 & 0.28 & 0.17 \\ 0.7 & 0.5 & 0.73 & 0.87 & 0.79 & 0.81 \\ 0.54 & 0.27 & 0.5 & 0.7 & 0.24 & 0.46 \\ 0.27 & 0.13 & 0.3 & 0.5 & 0.13 & 0.17 \\ 0.72 & 0.21 & 0.76 & 0.87 & 0.5 & 0.54 \\ 0.83 & 0.19 & 0.54 & 0.83 & 0.45 & 0.5 \end{pmatrix}$$

$$P^{(5)} = \begin{pmatrix} 0.5 & 0.65 & 0.45 & 0.15 & 0.6 & 0.4 \\ 0.35 & 0.5 & 0.8 & 0.75 & 0.3 & 0.7 \\ 0.55 & 0.2 & 0.5 & 0.55 & 0.6 & 0.45 \\ 0.85 & 0.25 & 0.45 & 0.5 & 0.9 & 0.6 \\ 0.4 & 0.7 & 0.4 & 0.1 & 0.5 & 0.7 \\ 0.6 & 0.3 & 0.55 & 0.4 & 0.3 & 0.5 \end{pmatrix}$$

$$P^{(6)} = \begin{pmatrix} 0.5 & 0.8 & 0.65 & 0.9 & 0.7 & 0.8 \\ 0.2 & 0.5 & 0.6 & 0.7 & 0.3 & 0.55 \\ 0.35 & 0.4 & 0.5 & 0.6 & 0.7 & 0.35 \\ 0.1 & 0.3 & 0.4 & 0.5 & 0.65 & 0.3 \\ 0.3 & 0.7 & 0.3 & 0.35 & 0.5 & 0.7 \\ 0.2 & 0.45 & 0.65 & 0.7 & 0.3 & 0.5 \end{pmatrix}$$

$$P^{(7)} = \begin{pmatrix} 0.5 & 0.44 & 0.35 & 0.81 & 0.76 & 0.83 \\ 0.56 & 0.5 & 0.2 & 0.27 & 0.79 & 0.9 \\ 0.65 & 0.8 & 0.5 & 0.9 & 0.86 & 0, 95 \\ 0.19 & 0.73 & 0.1 & 0.5 & 0.3 & 0.65 \\ 0.24 & 0.21 & 0.14 & 0.7 & 0.5 & 0.77 \\ 0.17 & 0.1 & 0.05 & 0.35 & 0.23 & 0.5 \end{pmatrix}$$

$$P^{(8)} = \begin{pmatrix} 0.5 & 0.22 & 0.38 & 0.43 & 0.63 & 0.11 \\ 0.78 & 0.5 & 0.56 & 0.73 & 0.85 & 0.33 \\ 0.62 & 0.44 & 0.5 & 0.7 & 0.73 & 0.75 \\ 0.57 & 0.27 & 0.3 & 0.5 & 0.6 & 0.9 \\ 0.37 & 0.15 & 0.27 & 0.4 & 0.5 & 0.77 \\ 0.89 & 0.67 & 0.25 & 0.1 & 0.23 & 0.5 \end{pmatrix}$$

At the same time, MMEMs are also established based on experts' mutual evaluations on each other considering seven attributes: cooperative attitude(a_1), reliability(a_2), cooperative ability(a_3), professional ability(a_4), fairness(a_5), not over adjustment(a_6), and not contingency(a_7). The original MMEMs are provided by the experts listed as below.

$$V^{(1,1)} = \begin{pmatrix} null & null & null & null & null & null & null \\ 85 & 86 & 88 & 99 & 94 & 91 & 94 \\ 89 & 98 & 96 & 93 & 93 & 99 & 89 \\ 100 & 96 & 98 & 89 & 93 & 99 & 88 \\ 93 & 92 & 98 & 99 & 89 & 99 & 96 \\ 90 & 97 & 90 & 99 & 97 & 96 & 100 \\ 86 & 97 & 86 & 100 & 93 & 85 & 95 \\ 92 & 85 & 90 & 87 & 100 & 92 & 99 \end{pmatrix}$$

$$V^{(2,1)} = \begin{pmatrix} 91 & 92 & 87 & 95 & 98 & 97 & 92 \\ null & null & null & null & null & null & null \\ 98 & 98 & 95 & 99 & 88 & 99 & 92 \\ 93 & 85 & 96 & 97 & 85 & 94 & 94 \\ 96 & 89 & 94 & 88 & 92 & 92 & 93 \\ 86 & 91 & 85 & 96 & 93 & 90 & 93 \\ 89 & 99 & 87 & 93 & 89 & 91 & 94 \\ 92 & 92 & 99 & 97 & 98 & 99 & 98 \end{pmatrix}$$

$$V^{(3,1)}=\begin{pmatrix} 87 & 95 & 85 & 85 & 86 & 97 & 91\\ 89 & 87 & 89 & 99 & 86 & 95 & 87\\ null & null & null & null & null & null & null\\ 100 & 86 & 93 & 96 & 85 & 97 & 91\\ 91 & 99 & 87 & 86 & 99 & 90 & 91\\ 91 & 85 & 86 & 91 & 92 & 97 & 85\\ 89 & 85 & 92 & 97 & 97 & 92 & 100\\ 85 & 86 & 99 & 85 & 87 & 94 & 93 \end{pmatrix}$$

$$V^{(4,1)}=\begin{pmatrix} 94 & 99 & 89 & 87 & 88 & 98 & 86\\ 97 & 92 & 96 & 96 & 89 & 87 & 85\\ 87 & 85 & 89 & 87 & 90 & 93 & 85\\ null & null & null & null & null & null & null\\ 85 & 96 & 93 & 97 & 94 & 86 & 98\\ 92 & 99 & 99 & 91 & 89 & 88 & 85\\ 95 & 86 & 89 & 98 & 98 & 93 & 98\\ 89 & 91 & 94 & 85 & 99 & 87 & 95 \end{pmatrix}$$

$$V^{(5,1)}=\begin{pmatrix} 85 & 94 & 92 & 93 & 98 & 90 & 87\\ 97 & 98 & 92 & 89 & 95 & 88 & 96\\ 87 & 95 & 91 & 85 & 100 & 88 & 93\\ 89 & 90 & 89 & 86 & 92 & 97 & 98\\ null & null & null & null & null & null & null\\ 87 & 98 & 95 & 95 & 85 & 90 & 85\\ 96 & 85 & 92 & 95 & 99 & 95 & 100\\ 100 & 96 & 86 & 85 & 93 & 96 & 97 \end{pmatrix}$$

$$V^{(6,1)}=\begin{pmatrix} 85 & 99 & 96 & 85 & 92 & 87 & 90\\ 94 & 85 & 92 & 89 & 99 & 99 & 87\\ 88 & 87 & 99 & 96 & 89 & 98 & 91\\ 88 & 97 & 85 & 99 & 96 & 92 & 90\\ 94 & 95 & 87 & 96 & 94 & 99 & 93\\ null & null & null & null & null & null & null\\ 97 & 96 & 94 & 97 & 96 & 94 & 89\\ 98 & 97 & 95 & 96 & 96 & 95 & 91 \end{pmatrix}$$

$$V^{(7,1)}=\begin{pmatrix} 86 & 98 & 95 & 100 & 98 & 88 & 85\\ 85 & 89 & 89 & 99 & 97 & 97 & 92\\ 93 & 97 & 86 & 92 & 96 & 90 & 94\\ 92 & 98 & 93 & 96 & 95 & 90 & 89\\ 86 & 91 & 94 & 92 & 98 & 97 & 86\\ 93 & 94 & 87 & 90 & 94 & 89 & 97\\ null & null & null & null & null & null & null\\ 93 & 91 & 89 & 99 & 87 & 100 & 90 \end{pmatrix}$$

$$V^{(8,1)}=\begin{pmatrix} 98 & 97 & 83 & 94 & 98 & 98 & 83\\ 97 & 88 & 85 & 95 & 96 & 95 & 78\\ 95 & 88 & 93 & 83 & 96 & 85 & 85\\ 92 & 92 & 94 & 93 & 96 & 85 & 86\\ 90 & 93 & 95 & 98 & 95 & 92 & 89\\ 85 & 95 & 95 & 96 & 93 & 98 & 97\\ 85 & 96 & 95 & 97 & 82 & 94 & 99\\ null & null & null & null & null & null & null \end{pmatrix}$$

(1) Based on $V^{(1,1)}$ to $V^{(8,1)}$, experts' weights are computed by (13) in the current example, as it shown in Table 5. In the first round, by (6), it is obtained that the initial consensus degree $cl^0 = 0.7284$. Denote $V^{(z,t)}$ as the MEEM of expert e_z in rount t, the MMEMs in round 1 are also the original MMEMs, that is to say, $V^{(z,1)} = V^{(z)}(z = 1, 2, \ldots, 8)$. And the collective preference relation $P^{(c,0)}$ is computed by (7) as below.

$$P^{(c,0)}=\begin{pmatrix} 0.5 & 0.5369 & 0.5008 & 0.5898 & 0.5294 & 0.6375\\ 0.4631 & 0.5 & 0.5661 & 0.5716 & 0.6128 & 0.6737\\ 0.4992 & 0.4339 & 0.5 & 0.6852 & 0.6042 & 0.6637\\ 0.4102 & 0.4284 & 0.3148 & 0.5 & 0.5635 & 0.5938\\ 0.4706 & 0.3872 & 0.3958 & 0.4365 & 0.5 & 0.6827\\ 0.3625 & 0.3263 & 0.3363 & 0.4062 & 0.3161 & 0.5 \end{pmatrix}$$

When $P^{(z,1)} = (p_{ij}^{(z,1)})_{n\times n}(z = 1, 2, \ldots, 8)$ is constructed, $p_{ij}^{(z,1)}$ is suggested to be adjusted to a value in interval $[p_{ij}^{(z,0)}, p_{ij}^{(c,0)}](i \le j)$, i.e., $p_{ij}^{(z,1)} \in [p_{ij}^{(z,0)}, p_{ij}^{(c,0)}](i \le j)$. However, in order to simulate better the real life situation, it should be noticed that not every expert will obey this suggestion. For instance, $p_{ij}^{(1,1)} = 0.3815 \notin [0.5005.0.9]$. Suppose that in round 1, experts' preference relations are adjusted as is shown in Appendix A(A.1). The collective preference relation after the adjustments in round 1 is denoted by $P^{(c,1)}$ and presented as below.

$$P^{(c,1)}=\begin{pmatrix} 0.5 & 0.6380 & 0.5465 & 0.6128 & 0.5096 & 0.6009\\ 0.3620 & 0.5 & 0.5872 & 0.5582 & 0.6076 & 0.6546\\ 0.4535 & 0.4128 & 0.5 & 0.5851 & 0.6385 & 0.6013\\ 0.3872 & 0.4418 & 0.4149 & 0.5 & 0.5921 & 0.5584\\ 0.4904 & 0.3924 & 0.3615 & 0.4079 & 0.5 & 0.6649\\ 0.3991 & 0.3454 & 0.3987 & 0.4416 & 0.3351 & 0.5 \end{pmatrix}$$

By applying (6), the consensus degree is achieved as $cl^1 = 0.8007$.

Based on $P^{(1,1)} - P^{(8,1)}$, according to the punish rules we set for non-cooperative behaviors, the experts'non-cooperative behavior matrix in round 1 is computed by (30) and shown as below, and the experts who perform non-cooperate behavior will be punished in the second round by decreasing their weights.

$$NC^{(1)}=\begin{pmatrix} 0&0&0&0&0&0&1\\ 1&0&0&0&0&0&1\\ 0&0&0&0&1&0&0\\ 0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0\\ 0&0&0&0&0&0&0\\ 0&0&0&0&1&0&1 \end{pmatrix}$$

Here, $NC_{ij}^{(1)} = 1$ indicates that expert e_i performs non-cooperative behavior j in round 1, while $NC_{ij}^{(1)} = 0$ indicates that expert e_i does not perform behavior j in round 1. Afterwards, the experts' weights are updated by applying (13) based on $V^{(1,1)}, V^{(2,1)}, \dots, V^{(8,1)}$, as is shown by Table 6.

(2) In round 2, when $P^{(z,2)} = (p_{ij}^{(z,2)})_{n\times n} (z = 1, 2, \dots, 8)$ is constructed, $p_{ij}^{(z,2)}$ is suggested to be adjusted to values in interval $[p_{ij}^{(z,1)}, p_{ij}^{(c,1)}]$ if $p_{ij}^{(z,1)} \le p_{ij}^{(c,1)}$), or $[p_{ij}^{(c,1)}, p_{ij}^{(z,1)}]$ if $p_{ij}^{(c,1)} \le p_{ij}^{(z,1)}$). In order to simulate better the real life situation, not every expert will obey this suggestion. For instance, $p_{ij}^{(8,2)} = 0.0314 \notin [0.512, 0.6475]$. Suppose that in round 2, experts' preference relations $P^{(z,2)} (z = 1, 2, \dots, 8)$ are adjusted as is shown in Appendix A(A.2). The collective preference relation after adjustments in round 2 is obtained as $P^{(c,2)}$,

$$P^{(c,2)} = \begin{pmatrix} 0.5 & 0.6175 & 0.5292 & 0.6016 & 0.4903 & 0.5071 \\ 0.3825 & 0.5 & 0.58977 & 0.5654 & 0.6499 & 0.6651 \\ 0.4708 & 0.4103 & 0.5 & 0.6210 & 0.6234 & 0.5883 \\ 0.3984 & 0.4346 & 0.3790 & 0.5 & 0.5293 & 0.5526 \\ 0.5097 & 0.3501 & 0.3766 & 0.4707 & 0.5 & 0.5179 \\ 0.4929 & 0.3349 & 0.41177 & 0.4474 & 0.4821 & 0.5 \end{pmatrix}$$

The non-cooperative behavior matrix of the experts in the second round, i.e., $NC^{(2)}$ is computed by (30) and shown as follows, and the weights of experts who do not cooperate will be punished in the third round.

$$NC^{(2)} = \begin{pmatrix} 0&0&0&1&0&0&0 \\ 1&0&0&1&0&0&0 \\ 0&0&1&0&0&0&1 \\ 0&0&0&0&1&0&0 \\ 1&0&0&0&0&0&1 \\ 1&0&0&0&0&0&0 \\ 0&0&0&0&0&0&1 \\ 0&0&0&0&0&0&1 \end{pmatrix}$$

According to $NC^{(2)}$, the MMEMs will be updated as below, by applying (31) and (32).

$$V^{(1,2)} = \begin{pmatrix} null & null & null & null & null & null & null \\ 59.5 & 86 & 88 & 99 & 75.2 & 91 & 84.6 \\ 89 & 98 & 96 & 93 & 74.4 & 99 & 89 \\ 100 & 96 & 98 & 89 & 74.4 & 99 & 88 \\ 93 & 92 & 98 & 99 & 71.2 & 99 & 96 \\ 90 & 97 & 90 & 99 & 77.6 & 96 & 100 \\ 86 & 97 & 86 & 100 & 93 & 85 & 95 \\ 92 & 85 & 90 & 87 & 64 & 92 & 89.1 \end{pmatrix}$$

$$V^{(2,2)} = \begin{pmatrix} 91 & 92 & 87 & 95 & 98 & 97 & 82.8 \\ null & null & null & null & null & null & null \\ 98 & 98 & 95 & 99 & 70.4 & 99 & 92 \\ 93 & 85 & 96 & 97 & 68 & 94 & 94 \\ 96 & 89 & 94 & 88 & 73.6 & 92 & 93 \\ 86 & 91 & 85 & 96 & 74.4 & 90 & 93 \\ 89 & 99 & 87 & 93 & 89 & 91 & 94 \\ 92 & 92 & 99 & 97 & 62.72 & 99 & 88.2 \end{pmatrix}$$

$$V^{(3,2)} = \begin{pmatrix} 87 & 95 & 85 & 85 & 86 & 97 & 81.9 \\ 62.3 & 87 & 89 & 99 & 68.8 & 95 & 78.3 \\ null & null & null & null & null & null & null \\ 100 & 86 & 93 & 96 & 68 & 97 & 91 \\ 91 & 99 & 87 & 86 & 79.2 & 90 & 91 \\ 91 & 85 & 86 & 91 & 73.6 & 97 & 85 \\ 89 & 85 & 92 & 97 & 97 & 92 & 100 \\ 85 & 86 & 99 & 85 & 55.68 & 94 & 83.7 \end{pmatrix}$$

$$V^{(4,2)} = \begin{pmatrix} 94 & 99 & 89 & 87 & 88 & 98 & 77.4 \\ 67.9 & 92 & 96 & 96 & 71.2 & 87 & 76.5 \\ 87 & 85 & 89 & 87 & 72 & 93 & 85 \\ null & null & null & null & null & null & null \\ 85 & 96 & 93 & 97 & 75.2 & 86 & 98 \\ 92 & 99 & 99 & 91 & 71.2 & 88 & 85 \\ 95 & 86 & 89 & 98 & 98 & 93 & 98 \\ 89 & 91 & 94 & 85 & 63.36 & 87 & 85.5 \end{pmatrix}$$

$$V^{(5,2)} = \begin{pmatrix} 85 & 94 & 92 & 93 & 98 & 90 & 78.3 \\ 67.9 & 98 & 92 & 89 & 76 & 88 & 86.4 \\ 87 & 95 & 91 & 85 & 80 & 88 & 93 \\ 89 & 90 & 89 & 86 & 73.6 & 97 & 98 \\ null & null & null & null & null & null & null \\ 87 & 98 & 95 & 95 & 68 & 90 & 85 \\ 96 & 85 & 92 & 95 & 99 & 95 & 100 \\ 100 & 96 & 86 & 85 & 59.52 & 96 & 87.3 \end{pmatrix}$$

$$V^{(6,2)} = \begin{pmatrix} 85 & 99 & 96 & 85 & 92 & 87 & 81 \\ 65.8 & 85 & 92 & 89 & 79.2 & 99 & 78.3 \\ 88 & 87 & 99 & 96 & 71.2 & 98 & 91 \\ 88 & 97 & 85 & 99 & 76.8 & 92 & 90 \\ 94 & 95 & 87 & 96 & 75.2 & 99 & 93 \\ null & null & null & null & null & null & null \\ 97 & 96 & 94 & 97 & 96 & 94 & 89 \\ 98 & 97 & 95 & 96 & 61.44 & 95 & 81.9 \end{pmatrix}$$

$$V^{(7,2)} = \begin{pmatrix} 86 & 98 & 95 & 100 & 98 & 88 & 76.5 \\ 59.5 & 89 & 89 & 99 & 77.6 & 97 & 82.8 \\ 93 & 97 & 86 & 92 & 76.8 & 90 & 94 \\ 92 & 98 & 93 & 96 & 76 & 90 & 89 \\ 86 & 91 & 94 & 92 & 78.4 & 97 & 86 \\ 93 & 94 & 87 & 90 & 75.2 & 89 & 97 \\ null & null & null & null & null & null & null \\ 93 & 91 & 89 & 99 & 55.68 & 100 & 81 \end{pmatrix}$$

$$V^{(8,2)} = \begin{pmatrix} 98 & 97 & 83 & 94 & 98 & 98 & 74.7 \\ 67.9 & 88 & 85 & 95 & 76.8 & 95 & 70.2 \\ 95 & 88 & 93 & 83 & 76.8 & 85 & 85 \\ 92 & 92 & 94 & 93 & 76.8 & 85 & 86 \\ 90 & 93 & 95 & 98 & 76 & 92 & 89 \\ 85 & 95 & 95 & 96 & 74.4 & 98 & 97 \\ 85 & 96 & 95 & 97 & 82 & 94 & 99 \\ null & null & null & null & null & null & null \end{pmatrix}$$

Experts' weights are updated based on $V^{(1,2)}, V^{(2,2)}, \ldots, V^{(8,2)}$, by applying (13), as is shown by Table 7.

We obtain that $cl^2 = 0.852 > \overline{cl}$, the consensus is reached. Afterwards, based on the collective preference in round 2, the collective ranking of alternatives is $x_2 > x_3 > x_1 > x_4 > x_5 > x_6$, so "SF Express" is suggested to be chosen finally.

6.3 The numerical comparison

A numerical comparison is carried out between the current proposal and the non-cooperate behaviors management strategy based on mutual score proposed by Dong et al. in [16]. The same consensus measure and feedback rule are adopted in both proposals. Whereas, the weight updating scheme based on mutual score in [16] and the scheme based on comprehensive score in the current proposal are applied, respectively. It should be noticed that the identification mechanisms are different, the one in the current proposal is more comprehensive than the one in [16], since only three types of non-cooperative behaviors can be figured out in [16], whereas 7 types can be identified in this paper. Among these 7 types, 3 types share the similar meaning, i.e.,"cooperate ability" is similar to "cooperation ","fairness" is similar to "fairness", "low professional level" is similar to "skill"("cooperation ", "fairness" and "skill" are features considered in [16]). To make the comparison feasible, we assume that the initial mutual scores provided by experts on these 3 features are the same. The initial MMEM for Dong et al's proposal can be rewritten here, for the convenience of readers to check. More computation details can be found in Appendix C. The performance of consensus models can be evaluated by different features such as, number of rounds, consensus level, etc. [47] It is shown by Fig. 6 the consensus degree in each round, and the consensus reaching needs less rounds by applying our proposed non-cooperative behaviors management scheme.

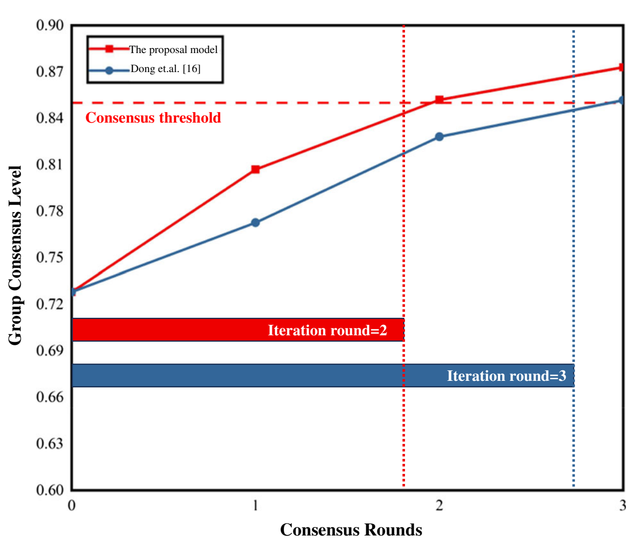

Fig. 6 The iteration and group consensus level based on two models

6.4 Discussion

As is shown by Fig. 6, by applying Dong et al's approach the consensus can be reached in 3 iteration rounds. By applying the proposed approach the consensus can be reached in 2 rounds, and the group consensus level in each round is higher. The reason for a quicker consensus reaching by applying the current proposal is that our proposal provides a more comprehensive recognize strategy, as well as a more effective management strategy for dealing with non-cooperate behaviors, by which both the performance in the current CRP round and historical performance can be considered, meanwhile the non-cooperate behaviors in different time periods can be handled in different manners.

Another experiment has been carried out to illustrate the advantage of the current proposal. Here, we carry out the CRP with the same penalty factor for different behaviors as $\theta(a_i)(i = 1, 2, \cdots, 7)$, and then compare the CRP with the case when $\theta(a_i)^*$ in Table 1 is applied. It is shown by Fig. 7 that the consensus can be reached in 2 rounds by applying different penalty factors indicated by $\theta(a_i)^*$, while 3 rounds are needed if the same penalty factor is used for different behaviors. Meanwhile, the group consensus level is higher in each rounds of the CRP. This means that the proposed scheme, which involves managing different behaviors differently, increases flexibility and, as a result, enhances the effectiveness of the CRP.

Sensitive analysis is conducted here to demonstrate how the different penalty factors corresponding to different non-cooperate behaviors affect the CRP. The value of a penalty factor $\theta(a_i)*$ is variet from $\{\theta(a_i)^* - 0.5, \theta(a_i)^* - 0.4, \cdots, \theta(a_i)^* + 0.4, \theta(a_i)^* + 0.5\}$, while keeping the penalty factor for other behaviors constant. In this research, seven types of non-cooperative behaviors have been identified. Therefore, the experiment is carried out seven times, each addressing one penal factor of these distinct behaviors. The results in Fig. 8 show that with $\theta(a_i)^*$ (see Table 1), the consensus level is higher in each round, that is also the reason why we set $\theta(a_i)^*$ as it is in Table 1. For instance, in each round the group consensus level

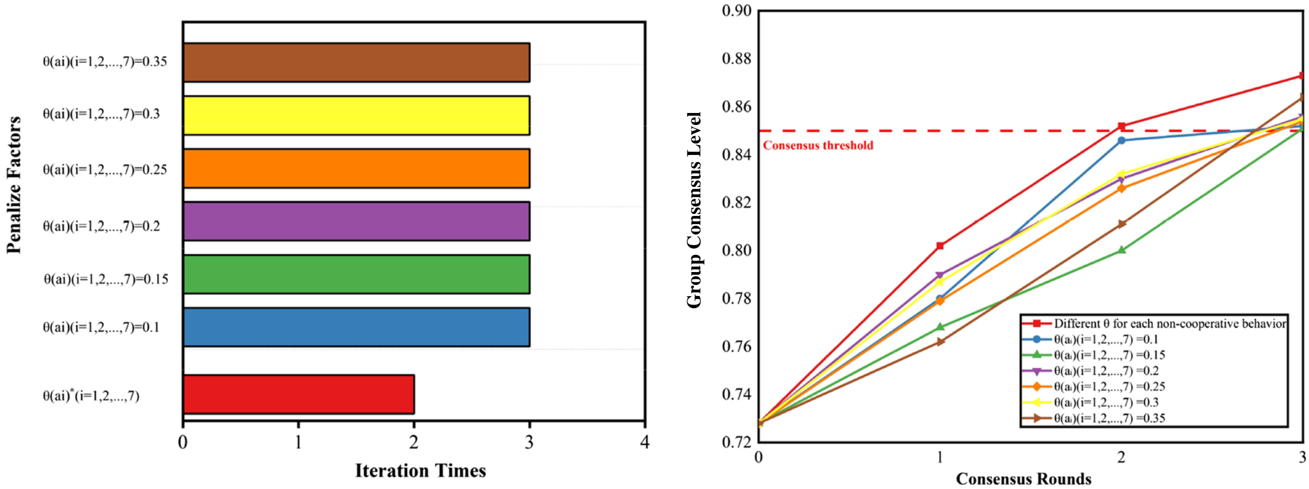

Fig. 7 CRP based on same and different penalty factors for various non-cooperative behaviors

when $\theta(a_1)^* = 0.3$ (see Fig. 8, subfigure (a))is always higher than the group consensus level when $\theta(a_1)^* = 0.25, 0.26, 0.27, 0.28, 0.29, 0.31, 0.32, 0.33, 0.34, 0.35$. The proposed mechanism allows for flexibility in choosing different penalty factors for different non-cooperative behaviors, and the value of $\theta(a_1)^*$ can be determined through such experiments.

7 Conclusion

This study presents an effective strategy for managing the non-cooperative behaviors of experts in GDM problems. The proposed mechanism determines experts' weights by identifying seven types of non-cooperative behaviors and developing different punishment strategies for each. Comprehensive scores are introduced by synthesizing the effects of non-cooperative behavior to enable different treatments of non-cooperative behavior in different periods of the CRP. The proposed consensus model based on a mutual comprehensive score matrix provides more persuasive preference adjustment directions before consensus is reached. To demonstrate the practical application of the proposed model, it is applied to solve a logistics enterprise selection problem. Comparative analysis with existing schemes addressing non-cooperative behaviors in GDM is conducted and it shows that the primary strength of the current work is that the identification of the non-cooperative behaviors is more comprehensive, and the strategy to address these behaviors is more flexible. The experiments results demonstrate that the efficiency of CRP can be enhanced by employing different penalty schemes for different behaviors.

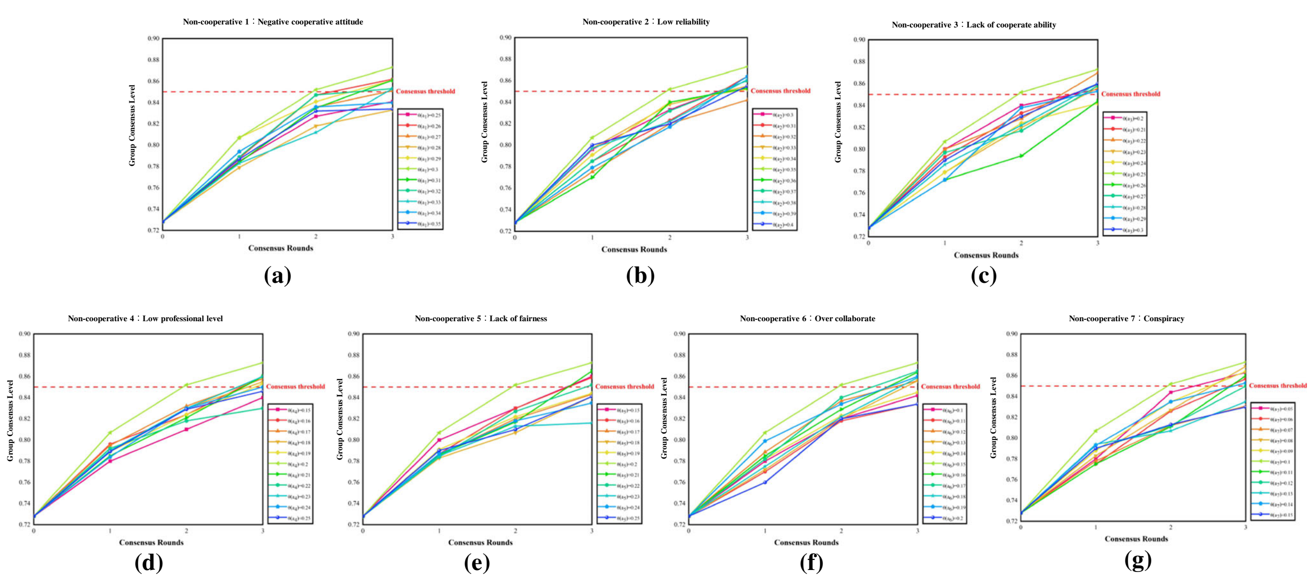

Fig. 8 Sensitive analysis

In future studies, the proposed non-cooperative behavior management strategies based on comprehensive score is suggested to be extended to handle large-scale GDM problems with more complex non-cooperative behaviors. To accommodate practical decision situations, it is also suggested to increase the diversity and flexibility of the linguistic information expression scope of experts.

Appendix A: Some figures and tables

A.1 List of mathematical notations

The list of mathematical notations in the proposed consensus model is presented by Table 4.

Table 4 List of mathematical notations in the proposed consensus model

Mathematical symbol	Meaning
$X = \{x_1, x_2, ..., x_n\}$	A set of alternatives
$E = \{e_1, e_2, ..., e_m\}$	A set of experts
NU	Null-norm operator
$W^t = (w^{(1,t)}, w^{(2,t)}, \ldots, w^{(m,t)})^T$	Weighting vector of experts in round t
$SM^{(zh,t)} = (sm_{ij}^{(zh,t)})_{n\times n}$	The similarity matrix for a pair of experts (e_z, e_h) in round t
cm_{ij}^t	The consensus level of the pair of alternatives (x_i, x_j) in round t
ca_i^t	The consensus level of all experts on alternative x_i in round t
cl^t	The consensus level of all experts on all alternatives in round t
$P^{(z,t)} = (p_{ij}^{(z,t)})_{n\times n}$	Fuzzy preference relation of expert e_z in round t
$P^{(c,t)} = (p_{ij}^{(c,t)})_{n\times n}$	The collective fuzzy preference relations in round t
$Pr^{(z,t)} = (pr_1^{(z,t)}, pr_2^{(z,t)}), \ldots, pr_n^{(z,t)})^T$	The fuzzy preference of expert e_z in round t
$Pr^{(c,t^*)} = (pr_1^{(c,t^*)}, pr_2^{(c,t^*)}), \ldots, pr_n^{(c,t^*)})^T$	The collective fuzzy preference after consensus reaching
$V^{(z,t)} = (v_{ij}^{(z,t)})_{m} \times_l$	The mutual evaluation matrices by expert e_z in round t
$\mu^{(z,t)}$	The mutual score of expert e_z in round t
$\sigma^{(z,t)}$	The comprehensive score of expert e_z in round t
$NC(a_l)\ l \in (1, 2, \ldots, 7)$	Identification coefficients for 7 non-cooperative behaviors
$\#ADV^{(z,t)}$	The number of preferences that e_z is advised to modify in round t
$\#ACP^{(z,t)}$	The number of preferences that e_z accepts to change in round t
$CC^{(z,t)}$	The cooperation coefficient of expert e_z in round t
$NCC^{(z,t)}$	The non-cooperation coefficient of expert e_z in round t
$D^{(z,t)}$	The adjustment amount of expert e_z in round t
$D_c^{(z,t)}$	The recommended adjustment amount of expert e_z in round t
$p_{ij}^{(a,t)}$	The average of group preferences on alternative x_i over x_j in round t
$O^{(z,t)} = (o^{(z,t)}(x_1), o_2^{(z,t)}(x_2), ..., o^{(z,t)}(x_n))^T$	The ranking vector of expert e_z in round t
$NC^{(t)}$	The non-cooperative matrix in round t

A.2 Figures for OPE function

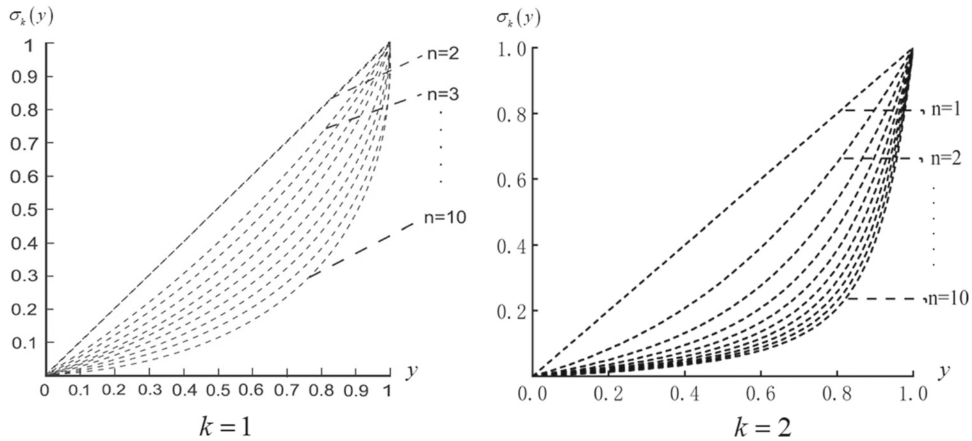

Fig. 9 OPE function σ_k with $k = 1$ and $k = 2$

A.3 Tables in the case study

Tables in the case study is presented as below (see Table 5 to Table 7).

Table 5 The original expert mutual evaluation score, comprehensive score and expert weight

Experts	Mutual Score(1)	Comprehensive Score(1)	Expert's weight(1)
e_1	0.1420	0.1420	0.1243
e_2	0.1419	0.1419	0.1242
e_3	0.1418	0.1418	0.1240
e_4	0.1429	0.1429	0.1251
e_5	0.1438	0.1438	0.1258
e_6	0.1425	0.1425	0.1247
e_7	0.1442	0.1442	0.1262
e_8	0.1438	0.1438	0.1258

Table 6 The first round of expert mutual evaluation score, comprehensive score and expert weight

Experts	Mutual Score(2)	Comprehensive Score(2)	Expert's weight(2)
e_1	0.1449	0.0563	0.1250
e_2	0.1402	0.0542	0.1238
e_3	0.1446	0.0562	0.1248
e_4	0.1412	0.0547	0.1246
e_5	0.1421	0.0550	0.1253
e_6	0.1408	0.0545	0.1243
e_7	0.1470	0.0573	0.1268
e_8	0.1420	0.0550	0.1253

Table 7 The second round of expert mutual evaluation score, comprehensive score and expert weight

Experts	Mutual Score(3)	Comprehensive Score(3)	Expert's weight(3)
e_1	0.1456	0.0341	0.1255
e_2	0.1344	0.0310	0.1226
e_3	0.1426	0.0333	0.1248
e_4	0.1438	0.0336	0.1249
e_5	0.1446	0.0338	0.1256
e_6	0.1434	0.0335	0.1245
e_7	0.1499	0.0353	0.1276
e_8	0.1386	0.0322	0.1245

Appendix B: Adjusted preference relation matrix during the CRP process

B1. Experts' adjusted preference relations in round 1.

$$P^{(1,1)} = \begin{pmatrix} 0.5 & 0.5524 & 0.9851 & 0.7522 & 0.4677 & 0.6381 \\ 0.4476 & 0.5 & 0.7952 & 0.5599 & 0.7749 & 0.7 \\ 0.0149 & 0.2048 & 0.5 & 0.6 & 0.6282 & 0.6765 \\ 0.2478 & 0.4401 & 0.4 & 0.5 & 0.5594 & 0.3394 \\ 0.5323 & 0.2251 & 0.3718 & 0.4406 & 0.5 & 0.6895 \\ 0.3619 & 0.3 & 0.3235 & 0.6606 & 0.3105 & 0.5 \end{pmatrix}$$

$$P^{(2,1)} = \begin{pmatrix} 0.5 & 0.6286 & 0.5619 & 0.5988 & 0.4 & 0.2869 \\ 0.3714 & 0.5 & 0.6654 & 0.4597 & 0.7205 & 0.6 \\ 0.4381 & 0.3346 & 0.5 & 0.6912 & 0.4829 & 0.6 \\ 0.4012 & 0.5403 & 0.3088 & 0.5 & 0.6924 & 0.7236 \\ 0.6 & 0.2795 & 0.5171 & 0.3076 & 0.5 & 0.4930 \\ 0.7131 & 0.4 & 0.4 & 0.2764 & 0.5070 & 0.5 \end{pmatrix}$$

$$P^{(3,1)} = \begin{pmatrix} 0.5 & 0.5900 & 0.4271 & 0.8215 & 0.4857 & 0.9 \\ 0.4100 & 0.5 & 0.5170 & 0.4635 & 0.4703 & 0.8 \\ 0.5729 & 0.4830 & 0.5 & 0.7154 & 0.6897 & 0.7144 \\ 0.1785 & 0.5365 & 0.2846 & 0.5 & 0.6812 & 0.7779 \\ 0.5143 & 0.5297 & 0.3103 & 0.3188 & 0.5 & 0.7061 \\ 0.1 & 0.2 & 0.2856 & 0.2221 & 0.2939 & 0.5 \end{pmatrix}$$

$$P^{(4,1)} = \begin{pmatrix} 0.5 & 0.3268 & 0.4787 & 0.66767 & 0.2700 & 0.7997 \\ 0.6732 & 0.5 & 0.5810 & 0.8282 & 0.6554 & 0.7636 \\ 0.5213 & 0.4190 & 0.5 & 0.6935 & 0.4719 & 0.4600 \\ 0.3324 & 0.1718 & 0.3065 & 0.5 & 0.3586 & 0.1700 \\ 0.7300 & 0.3446 & 0.5281 & 0.6414 & 0.5 & 0.5920 \\ 0.2003 & 0.2364 & 0.5400 & 0.8300 & 0.4080 & 0.5 \end{pmatrix}$$

$$P^{(5,1)} = \begin{pmatrix} 0.5 & 0.5944 & 0.4500 & 0.4621 & 0.5602 & 0.5212 \\ 0.4056 & 0.5 & 0.7846 & 0.1825 & 0.3 & 0.7 \\ 0.5500 & 0.2154 & 0.5 & 0.2532 & 0.6010 & 0.5153 \\ 0.5379 & 0.8175 & 0.7468 & 0.5 & 0.8399 & 0.5971 \\ 0.4398 & 0.7 & 0.3990 & 0.1601 & 0.5 & 0.6852 \\ 0.4788 & 0.3 & 0.4847 & 0.4029 & 0.3148 & 0.5 \end{pmatrix}$$

$$P^{(6,1)} = \begin{pmatrix} 0.5 & 0.6548 & 0.5566 & 0.4595 & 0.6253 & 0.7818 \\ 0.3452 & 0.5 & 0.6 & 0.6854 & 0.4361 & 0.6148 \\ 0.4434 & 0.4 & 0.5 & 0.6664 & 0.6910 & 0.3500 \\ 0.5405 & 0.3146 & 0.3336 & 0.5 & 0.6081 & 0.3904 \\ 0.3747 & 0.5639 & 0.3090 & 0.3919 & 0.5 & 0.6842 \\ 0.2182 & 0.3852 & 0.6500 & 0.6096 & 0.3158 & 0.5 \end{pmatrix}$$

$$P^{(7,1)} = \begin{pmatrix} 0.5 & 0.8679 & 0.4730 & 0.7049 & 0.6814 & 0.7477 \\ 0.1321 & 0.5 & 0.2 & 0.5693 & 0.7900 & 0.7282 \\ 0.5270 & 0.8 & 0.5 & 0.9 & 0.8094 & 0.7511 \\ 0.2951 & 0.4307 & 0.1 & 0.5 & 0.4223 & 0.6235 \\ 0.3186 & 0.2100 & 0.1906 & 0.5777 & 0.5 & 0.7022 \\ 0.2523 & 0.2718 & 0.2489 & 0.3765 & 0.2978 & 0.5 \end{pmatrix}$$

$$P^{(8,1)} = \begin{pmatrix} 0.5 & 0.8842 & 0.4413 & 0.4348 & 0.5822 & 0.1302 \\ 0.1158 & 0.5 & 0.5600 & 0.7177 & 0.7111 & 0.3300 \\ 0.5587 & 0.4400 & 0.5 & 0.1610 & 0.7300 & 0.7392 \\ 0.5652 & 0.2823 & 0.8390 & 0.5 & 0.5771 & 0.8434 \\ 0.4178 & 0.2889 & 0.2700 & 0.4229 & 0.5 & 0.7643 \\ 0.8698 & 0.6700 & 0.2608 & 0.1566 & 0.2357 & 0.5 \end{pmatrix}$$

B2. Experts' adjusted preference relations in round 2.

$$P^{(1,2)} = \begin{pmatrix} 0.5 & 0.5921 & 0.6919 & 0.6366 & 0.5082 & 0.6026 \\ 0.4079 & 0.5 & 0.6836 & 0.5592 & 0.9733 & 0.6973 \\ 0.3081 & 0.3164 & 0.5 & 0.6 & 0.6316 & 0.6434 \\ 0.3634 & 0.4408 & 0.4 & 0.5 & 0.5603 & 0.4603 \\ 0.4918 & 0.0267 & 0.3684 & 0.4397 & 0.5 & 0.6820 \\ 0.3974 & 0.3027 & 0.3566 & 0.5397 & 0.3180 & 0.5 \end{pmatrix}$$

$$P^{(2,2)} = \begin{pmatrix} 0.5 & 0.6288 & 0.5507 & 0.5988 & 0.4393 & 0.2869 \\ 0.3712 & 0.5 & 0.6654 & 0.5031 & 0.7186 & 0.6126 \\ 0.4493 & 0.3346 & 0.5 & 0.5913 & 0.5680 & 0.6008 \\ 0.4012 & 0.4969 & 0.4087 & 0.5 & 0.6191 & 0.7098 \\ 0.5607 & 0.2814 & 0.4320 & 0.3809 & 0.5 & 0.2022 \\ 0.7131 & 0.3874 & 0.3992 & 0.2902 & 0.7978 & 0.5 \end{pmatrix}$$

$$P^{(3,2)} = \begin{pmatrix} 0.5 & 0.5902 & 0.5332 & 0.8129 & 0.4996 & 0.0301 \\ 0.4098 & 0.5 & 0.5227 & 0.5205 & 0.5908 & 0.7988 \\ 0.4668 & 0.4773 & 0.5 & 0.7154 & 0.6618 & 0.6104 \\ 0.1871 & 0.4795 & 0.2846 & 0.5 & 0.6608 & 0.6184 \\ 0.5004 & 0.4092 & 0.3382 & 0.3392 & 0.5 & 0.3346 \\ 0.9699 & 0.2012 & 0.3896 & 0.3816 & 0.6654 & 0.5 \end{pmatrix}$$

$$P^{(4,2)} = \begin{pmatrix} 0.5 & 0.3929 & 0.5032 & 0.6332 & 0.3605 & 0.7997 \\ 0.6071 & 0.5 & 0.5816 & 0.6707 & 0.6364 & 0.6727 \\ 0.4968 & 0.4184 & 0.5 & 0.8046 & 0.5525 & 0.4600 \\ 0.3668 & 0.3293 & 0.1954 & 0.5 & 0.4557 & 0.2567 \\ 0.6395 & 0.3636 & 0.4475 & 0.5443 & 0.5 & 0.5975 \\ 0.2003 & 0.3273 & 0.5400 & 0.7433 & 0.4025 & 0.5 \end{pmatrix}$$

$$P^{(5,2)} = \begin{pmatrix} 0.5 & 0.6210 & 0.4500 & 0.5768 & 0.5310 & 0.5541 \\ 0.3790 & 0.5 & 0.7124 & 0.3109 & 0.3860 & 0.6754 \\ 0.5500 & 0.2876 & 0.5 & 0.2845 & 0.6010 & 0.5345 \\ 0.4232 & 0.6891 & 0.7155 & 0.5 & 0.3357 & 0.4907 \\ 0.4690 & 0.6140 & 0.3990 & 0.6643 & 0.5 & 0.6852 \\ 0.4459 & 0.3246 & 0.4655 & 0.5093 & 0.3148 & 0.5 \end{pmatrix}$$

$$P^{(6,2)} = \begin{pmatrix} 0.5 & 0.6411 & 0.4562 & 0.4847 & 0.6253 & 0.7293 \\ 0.3589 & 0.5 & 0.5975 & 0.6854 & 0.5979 & 0.6322 \\ 0.5438 & 0.4025 & 0.5 & 0.6664 & 0.6386 & 0.4373 \\ 0.5153 & 0.3146 & 0.3336 & 0.5 & 0.6066 & 0.4561 \\ 0.3747 & 0.4021 & 0.3614 & 0.3934 & 0.5 & 0.6808 \\ 0.2707 & 0.3678 & 0.5627 & 0.5439 & 0.3192 & 0.5 \end{pmatrix}$$

$$P^{(7,2)} = \begin{pmatrix} 0.5 & 0.7950 & 0.5414 & 0.4659 & 0.5106 & 0.7324 \\ 0.2050 & 0.5 & 0.3869 & 0.5605 & 0.6790 & 0.7058 \\ 0.4586 & 0.6131 & 0.5 & 0.7403 & 0.6828 & 0.7136 \\ 0.5341 & 0.4395 & 0.2597 & 0.5 & 0.4223 & 0.5886 \\ 0.4894 & 0.3210 & 0.3172 & 0.5777 & 0.5 & 0.2499 \\ 0.2676 & 0.2942 & 0.2864 & 0.4114 & 0.7501 & 0.5 \end{pmatrix}$$

$$P^{(8,2)} = \begin{pmatrix} 0.5 & 0.6757 & 0.5064 & 0.6063 & 0.4466 & 0.3118 \\ 0.3243 & 0.5 & 0.5723 & 0.7142 & 0.6173 & 0.5238 \\ 0.4936 & 0.4277 & 0.5 & 0.5645 & 0.6491 & 0.7040 \\ 0.3937 & 0.2858 & 0.4355 & 0.5 & 0.5790 & 0.8434 \\ 0.5534 & 0.3827 & 0.3509 & 0.4210 & 0.5 & 0.7104 \\ 0.6882 & 0.4762 & 0.2960 & 0.1566 & 0.2896 & 0.5 \end{pmatrix}$$

Appendix C: Computation process when Dong et al's approach is applied

C1. Experts' adjusted preference relations and MMEMs in round 2.

$$P^{(1,2)} = \begin{pmatrix} 0.5 & 0.6 & 0.4958 & 0.8105 & 0.4 & 0.9 \\ 0.4 & 0.5 & 0.7250 & 0.5683 & 0.9 & 0.6726 \\ 0.5042 & 0.2750 & 0.5 & 0.5966 & 0.5994 & 0.6570 \\ 0.1895 & 0.4317 & 0.4034 & 0.5 & 0.5714 & 0.3 \\ 0.6 & 0.1 & 0.4006 & 0.4286 & 0.5 & 0.6887 \\ 0.1 & 0.3274 & 0.3430 & 0.7 & 0.3113 & 0.5 \end{pmatrix}$$

$$P^{(2,2)} = \begin{pmatrix} 0.5 & 0.5969 & 0.8094 & 0.5896 & 0.4 & 0.6191 \\ 0.4031 & 0.5 & 0.5649 & 0.4 & 0.6021 & 0.6771 \\ 0.1906 & 0.4351 & 0.5 & 0.7 & 0.3 & 0.6679 \\ 0.4104 & 0.6 & 0.3 & 0.5 & 0.8013 & 0.9 \\ 0.6 & 0.3979 & 0.7 & 0.1987 & 0.5 & 0.2987 \\ 0.3809 & 0.3229 & 0.3321 & 0.1 & 0.7013 & 0.5 \end{pmatrix}$$

$$P^{(3,2)} = \begin{pmatrix} 0.5 & 0.5925 & 0.2006 & 0.5152 & 0.4695 & 0.9 \\ 0.4075 & 0.5 & 0.1400 & 0.2500 & 0.1700 & 0.7305 \\ 0.7994 & 0.8600 & 0.5 & 0.7323 & 0.6786 & 0.9729 \\ 0.4848 & 0.7500 & 0.2677 & 0.5 & 0.5617 & 0.9300 \\ 0.5305 & 0.8300 & 0.3214 & 0.4383 & 0.5 & 0.9194 \\ 0.1 & 0.2695 & 0.0271 & 0.0700 & 0.0806 & 0.5 \end{pmatrix}$$

$$P^{(4,2)} = \begin{pmatrix} 0.5 & 0.2919 & 0.4600 & 0.7300 & 0.2700 & 0.6742 \\ 0.7081 & 0.5 & 0.7300 & 0.7095 & 0.7900 & 0.8213 \\ 0.5400 & 0.2700 & 0.5 & 0.6842 & 0.2118 & 0.4556 \\ 0.2700 & 0.2905 & 0.3158 & 0.5 & 0.1097 & 0.6056 \\ 0.7300 & 0.2100 & 0.7882 & 0.8903 & 0.5 & 0.5400 \\ 0.3258 & 0.1787 & 0.5444 & 0.3944 & 0.4600 & 0.5 \end{pmatrix}$$

$$P^{(5,2)} = \begin{pmatrix} 0.5 & 0.6522 & 0.4869 & 0.1353 & 0.6012 & 0.4 \\ 0.3478 & 0.5 & 0.8 & 0.5533 & 0.3 & 0.7 \\ 0.5131 & 0.2 & 0.5 & 0.5500 & 0.6 & 0.6726 \\ 0.8647 & 0.4467 & 0.4500 & 0.5 & 0.9 & 0.6 \\ 0.3988 & 0.7 & 0.4 & 0.1 & 0.5 & 0.7018 \\ 0.6 & 0.3 & 0.3274 & 0.4 & 0.2982 & 0.5 \end{pmatrix}$$

$$P^{(6,2)} = \begin{pmatrix} 0.5 & 0.8 & 0.6500 & 0.9142 & 0.7104 & 0.6268 \\ 0.2 & 0.5 & 0.6 & 0.7 & 0.2898 & 0.5500 \\ 0.3500 & 0.4 & 0.5 & 0.6 & 0.6212 & 0.6734 \\ 0.0858 & 0.3 & 0.4 & 0.5 & 0.5568 & 0.3000 \\ 0.2896 & 0.7102 & 0.3788 & 0.4432 & 0.5 & 0.7 \\ 0.3732 & 0.4500 & 0.3266 & 0.7000 & 0.3 & 0.5 \end{pmatrix}$$

$$P^{(7,2)} = \begin{pmatrix} 0.5 & 0.4400 & 0.5029 & 0.8100 & 0.7600 & 0.6915 \\ 0.5600 & 0.5 & 0.5801 & 0.5937 & 0.7900 & 0.9136 \\ 0.4971 & 0.4199 & 0.5 & 0.9000 & 0.8768 & 0.9500 \\ 0.1900 & 0.4063 & 0.1000 & 0.5 & 0.5749 & 0.5939 \\ 0.2400 & 0.2100 & 0.1232 & 0.4251 & 0.5 & 0.7767 \\ 0.3085 & 0.0864 & 0.0500 & 0.4061 & 0.2233 & 0.5 \end{pmatrix}$$

$$P^{(8,2)} = \begin{pmatrix} 0.5 & 0.2200 & 0.3800 & 0.4300 & 0.5283 & 0.3451 \\ 0.7800 & 0.5 & 0.5600 & 0.7400 & 0.8500 & 0.3241 \\ 0.6200 & 0.4400 & 0.5 & 0.6846 & 0.6018 & 0.7407 \\ 0.5700 & 0.2600 & 0.3154 & 0.5 & 0.5625 & 0.9 \\ 0.4717 & 0.1500 & 0.3982 & 0.4375 & 0.5 & 0.7740 \\ 0.6549 & 0.6759 & 0.2593 & 0.1 & 0.2260 & 0.5 \end{pmatrix}$$

$$V^{(1,2)} = \begin{pmatrix} null & null & null \\ 88 & 94 & 99 \\ 96 & 93 & 93 \\ 98 & 93 & 89 \\ 98 & 89 & 99 \\ 90 & 97 & 99 \\ 86 & 93 & 100 \\ 90 & 100 & 87 \end{pmatrix} \quad V^{(2,2)} = \begin{pmatrix} 87 & 98 & 95 \\ null & null & null \\ 95 & 88 & 99 \\ 96 & 85 & 97 \\ 94 & 92 & 88 \\ 85 & 93 & 96 \\ 87 & 89 & 93 \\ 99 & 98 & 97 \end{pmatrix}$$

$$V^{(3,2)}=\begin{pmatrix}85&86&85\\89&86&99\\null&null&null\\93&85&96\\87&99&86\\86&92&91\\92&97&97\\99&87&85\end{pmatrix}\quad V^{(4,2)}=\begin{pmatrix}89&88&87\\96&89&96\\89&90&87\\null&null&null\\93&94&97\\99&89&91\\89&98&98\\94&99&85\end{pmatrix}$$

$$V^{(5,2)}=\begin{pmatrix}92&98&93\\92&95&89\\91&100&85\\89&92&86\\null&null&null\\95&85&95\\92&99&95\\86&93&85\end{pmatrix}\quad V^{(6,2)}=\begin{pmatrix}96&92&85\\92&99&89\\99&89&96\\85&96&99\\87&94&96\\null&null&null\\94&96&97\\95&96&96\end{pmatrix}$$

$$V^{(7,2)}=\begin{pmatrix}95&98&100\\89&97&99\\86&96&92\\93&95&96\\94&98&92\\87&94&90\\null&null&null\\89&87&99\end{pmatrix}\quad V^{(8,2)}=\begin{pmatrix}83&98&94\\85&96&95\\93&96&83\\94&96&93\\95&95&98\\95&93&96\\95&82&97\\null&null&null\end{pmatrix}$$

C2. Experts' adjusted preference relations and MMEMs in round 3.

$$P^{(1,3)}=\begin{pmatrix}0.5&0.5220&0.4958&0.8105&0.5282&0.6467\\0.4780&0.5&0.7250&0.5683&0.5721&0.6726\\0.5042&0.2750&0.5&0.5885&0.5994&0.6516\\0.1895&0.4317&0.4115&0.5&0.5714&0.2925\\0.4718&0.4279&0.4006&0.4286&0.5&0.6887\\0.3533&0.3274&0.3484&0.7075&0.3113&0.5\end{pmatrix}$$

$$P^{(2,3)}=\begin{pmatrix}0.5&0.5972&0.4956&0.5864&0.4000&0.6191\\0.4028&0.5&0.5649&0.4000&0.5913&0.6771\\0.5044&0.4351&0.5&0.7000&0.5714&0.6679\\0.4136&0.6000&0.3000&0.5&0.5636&0.9218\\0.6000&0.4087&0.4286&0.4364&0.5&0.2925\\0.3809&0.3229&0.3321&0.0782&0.7075&0.5\end{pmatrix}$$

$$P^{(3,3)}=\begin{pmatrix}0.5&0.5973&0.2006&0.5152&0.4938&0.6386\\0.4027&0.5&0.1400&0.2334&0.1700&0.7305\\0.7994&0.8600&0.5&0.6817&0.5568&0.9729\\0.4848&0.7666&0.3183&0.5&0.5612&0.9300\\0.5062&0.8300&0.4432&0.4388&0.5&0.9194\\0.3614&0.2695&0.0271&0.0700&0.0806&0.5\end{pmatrix}$$

$$P^{(4,3)}=\begin{pmatrix}0.5&0.2839&0.4593&0.6206&0.2700&0.6457\\0.7161&0.5&0.7315&0.5636&0.6236&0.8313\\0.5407&0.2685&0.5&0.6821&0.2118&0.4385\\0.3794&0.4364&0.3179&0.5&0.2381&0.6056\\0.7300&0.3764&0.7882&0.7619&0.5&0.5759\\0.3543&0.1687&0.5615&0.3944&0.4241&0.5\end{pmatrix}$$

$$P^{(5,3)}=\begin{pmatrix}0.5&0.6432&0.4869&0.6391&0.5986&0.4000\\0.3568&0.5&0.8075&0.5670&0.2916&0.7000\\0.5131&0.1925&0.5&0.6854&0.5957&0.6694\\0.3609&0.4330&0.3146&0.5&0.9000&0.5996\\0.4014&0.7084&0.4043&0.1000&0.5&0.6682\\0.6000&0.3000&0.3306&0.4004&0.3318&0.5\end{pmatrix}$$

$$P^{(6,3)}=\begin{pmatrix}0.5&0.8261&0.4920&0.7864&0.5108&0.6490\\0.1739&0.5&0.6000&0.5572&0.5783&0.5420\\0.5080&0.4000&0.5&0.6833&0.6212&0.6734\\0.2136&0.4428&0.3167&0.5&0.5568&0.2857\\0.4892&0.4217&0.3788&0.4432&0.5&0.7003\\0.3510&0.4580&0.3266&0.7143&0.2997&0.5\end{pmatrix}$$

$$P^{(7,3)}=\begin{pmatrix}0.5&0.4400&0.5035&0.8100&0.7600&0.6915\\0.5600&0.5&0.5801&0.5948&0.8004&0.9136\\0.4965&0.4199&0.5&0.8968&0.8808&0.7006\\0.1900&0.4052&0.1032&0.5&0.5749&0.5939\\0.2400&0.1996&0.1192&0.4251&0.5&0.7767\\0.3085&0.0864&0.2994&0.4061&0.2233&0.5\end{pmatrix}$$

$$P^{(8,3)}=\begin{pmatrix}0.5&0.5467&0.3800&0.4300&0.5283&0.3451\\0.4533&0.5&0.5600&0.7436&0.8500&0.6903\\0.6200&0.4400&0.5&0.6829&0.6040&0.7207\\0.5700&0.2564&0.3171&0.5&0.5617&0.6346\\0.4717&0.1500&0.3960&0.4383&0.5&0.7199\\0.6549&0.3097&0.2793&0.3654&0.2801&0.5\end{pmatrix}$$

$$V^{(1,3)}=\begin{pmatrix}null&null&null\\88&74&99\\96&73&73\\98&73&89\\98&69&79\\90&77&99\\86&73&100\\90&80&67\end{pmatrix}\quad V^{(2,3)}=\begin{pmatrix}87&78&95\\null&null&null\\95&68&79\\96&65&97\\94&72&68\\85&73&96\\87&69&93\\99&78&77\end{pmatrix}$$

$$V^{(3,3)}=\begin{pmatrix}85&66&85\\89&66&99\\null&null&null\\93&65&96\\87&79&66\\86&72&91\\92&77&97\\99&67&85\end{pmatrix}\quad V^{(4,3)}=\begin{pmatrix}89&68&87\\96&69&96\\89&70&87\\null&null&null\\93&74&77\\99&69&91\\89&78&98\\94&79&65\end{pmatrix}$$

$$V^{(5,3)}=\begin{pmatrix}92&78&93\\92&75&89\\91&80&65\\89&72&86\\null&null&null\\95&65&95\\92&79&95\\86&73&65\end{pmatrix}\quad V^{(6,3)}=\begin{pmatrix}96&72&85\\92&79&89\\99&69&76\\85&76&99\\87&74&76\\null&null&null\\94&76&97\\95&76&76\end{pmatrix}$$

$$V^{(7,3)} = \begin{pmatrix} 95 & 78 & 100 \\ 89 & 77 & 99 \\ 86 & 76 & 72 \\ 93 & 75 & 96 \\ 94 & 78 & 72 \\ 87 & 74 & 90 \\ null & null & null \\ 89 & 67 & 79 \end{pmatrix} \quad V^{(8,3)} = \begin{pmatrix} 83 & 78 & 94 \\ 85 & 76 & 95 \\ 93 & 76 & 63 \\ 94 & 76 & 93 \\ 95 & 75 & 78 \\ 95 & 73 & 96 \\ 95 & 62 & 97 \\ null & null & null \end{pmatrix}$$

C3. Experts' adjusted preference relations and MMEMs in round 4.

$$P^{(1,4)} = \begin{pmatrix} 0.5 & 0.5216 & 0.4958 & 0.8105 & 0.5198 & 0.6467 \\ 0.4784 & 0.5 & 0.7250 & 0.5683 & 0.5724 & 0.7193 \\ 0.5042 & 0.2750 & 0.5 & 0.5885 & 0.5800 & 0.6850 \\ 0.1895 & 0.4317 & 0.4115 & 0.5 & 0.5719 & 0.4713 \\ 0.4802 & 0.4276 & 0.4200 & 0.4281 & 0.5 & 0.6887 \\ 0.3533 & 0.2807 & 0.3150 & 0.5287 & 0.3113 & 0.5 \end{pmatrix}$$

$$P^{(2,4)} = \begin{pmatrix} 0.5 & 0.5972 & 0.4376 & 0.5864 & 0.3985 & 0.6227 \\ 0.4028 & 0.5 & 0.5649 & 0.4000 & 0.5914 & 0.6736 \\ 0.5624 & 0.4351 & 0.5 & 0.7000 & 0.5714 & 0.6679 \\ 0.4136 & 0.6000 & 0.3000 & 0.5 & 0.5633 & 0.9218 \\ 0.6015 & 0.4086 & 0.4286 & 0.4367 & 0.5 & 0.2925 \\ 0.3773 & 0.3264 & 0.3321 & 0.0782 & 0.7075 & 0.5 \end{pmatrix}$$

$$P^{(3,4)} = \begin{pmatrix} 0.5 & 0.5973 & 0.3246 & 0.5152 & 0.4938 & 0.6386 \\ 0.4027 & 0.5 & 0.1018 & 0.2962 & 0.1700 & 0.7305 \\ 0.6754 & 0.8982 & 0.5 & 0.6816 & 0.5607 & 0.9968 \\ 0.4848 & 0.7038 & 0.3184 & 0.5 & 0.5612 & 0.9401 \\ 0.5062 & 0.8300 & 0.4393 & 0.4388 & 0.5 & 0.8228 \\ 0.3614 & 0.2695 & 0.0032 & 0.0599 & 0.1772 & 0.5 \end{pmatrix}$$

$$P^{(4,4)} = \begin{pmatrix} 0.5 & 0.2839 & 0.4607 & 0.6370 & 0.2700 & 0.6457 \\ 0.7161 & 0.5 & 0.7336 & 0.5636 & 0.6236 & 0.8078 \\ 0.5393 & 0.2664 & 0.5 & 0.6821 & 0.4025 & 0.4143 \\ 0.3630 & 0.4364 & 0.3179 & 0.5 & 0.2148 & 0.6057 \\ 0.7300 & 0.3764 & 0.5975 & 0.7852 & 0.5 & 0.6736 \\ 0.3543 & 0.1922 & 0.5857 & 0.3943 & 0.3264 & 0.5 \end{pmatrix}$$

$$P^{(5,4)} = \begin{pmatrix} 0.5 & 0.6432 & 0.4413 & 0.6530 & 0.5986 & 0.3970 \\ 0.3568 & 0.5 & 0.8075 & 0.5670 & 0.2818 & 0.7192 \\ 0.5587 & 0.1925 & 0.5 & 0.6874 & 0.5957 & 0.6694 \\ 0.3470 & 0.4330 & 0.3126 & 0.5 & 0.9000 & 0.5991 \\ 0.4014 & 0.7182 & 0.4043 & 0.1000 & 0.5 & 0.6682 \\ 0.6030 & 0.2808 & 0.3306 & 0.4009 & 0.3318 & 0.5 \end{pmatrix}$$

$$P^{(6,4)} = \begin{pmatrix} 0.5 & 0.8261 & 0.4933 & 0.7670 & 0.5108 & 0.6503 \\ 0.1739 & 0.5 & 0.5949 & 0.5344 & 0.5665 & 0.5420 \\ 0.5067 & 0.4051 & 0.5 & 0.6826 & 0.6216 & 0.6734 \\ 0.2330 & 0.4656 & 0.3174 & 0.5 & 0.5604 & 0.4299 \\ 0.4892 & 0.4335 & 0.3784 & 0.4396 & 0.5 & 0.6632 \\ 0.3497 & 0.4580 & 0.3266 & 0.5701 & 0.3368 & 0.5 \end{pmatrix}$$

$$P^{(7,4)} = \begin{pmatrix} 0.5 & 0.4400 & 0.5035 & 0.6509 & 0.4935 & 0.6916 \\ 0.5600 & 0.5 & 0.5798 & 0.5990 & 0.5520 & 0.9136 \\ 0.4965 & 0.4202 & 0.5 & 0.6907 & 0.8924 & 0.7006 \\ 0.3491 & 0.4010 & 0.3093 & 0.5 & 0.5749 & 0.5939 \\ 0.5065 & 0.4480 & 0.1076 & 0.4251 & 0.5 & 0.7767 \\ 0.3084 & 0.0864 & 0.2994 & 0.4061 & 0.2233 & 0.5 \end{pmatrix}$$

$$P^{(8,4)} = \begin{pmatrix} 0.5 & 0.5467 & 0.3790 & 0.4300 & 0.5283 & 0.3389 \\ 0.4533 & 0.5 & 0.5600 & 0.7479 & 0.8500 & 0.7181 \\ 0.6210 & 0.4400 & 0.5 & 0.6995 & 0.6040 & 0.6813 \\ 0.5700 & 0.2521 & 0.3005 & 0.5 & 0.5667 & 0.6374 \\ 0.4717 & 0.1500 & 0.3960 & 0.4333 & 0.5 & 0.6645 \\ 0.6611 & 0.2819 & 0.3187 & 0.3626 & 0.3355 & 0.5 \end{pmatrix}$$

$$V^{(1,4)} = \begin{pmatrix} null & null & null \\ 88 & 54 & 99 \\ 96 & 53 & 53 \\ 98 & 53 & 89 \\ 98 & 49 & 79 \\ 90 & 77 & 99 \\ 86 & 53 & 100 \\ 90 & 80 & 67 \end{pmatrix} \quad V^{(2,4)} = \begin{pmatrix} 87 & 78 & 95 \\ null & null & null \\ 95 & 48 & 59 \\ 96 & 45 & 97 \\ 94 & 52 & 68 \\ 85 & 73 & 96 \\ 87 & 49 & 93 \\ 99 & 78 & 77 \end{pmatrix}$$

$$V^{(3,4)} = \begin{pmatrix} 85 & 66 & 85 \\ 89 & 46 & 99 \\ null & null & null \\ 93 & 45 & 96 \\ 87 & 59 & 66 \\ 86 & 72 & 91 \\ 92 & 57 & 97 \\ 99 & 67 & 85 \end{pmatrix} \quad V^{(4,4)} = \begin{pmatrix} 89 & 68 & 87 \\ 96 & 49 & 96 \\ 89 & 50 & 67 \\ null & null & null \\ 93 & 54 & 77 \\ 99 & 69 & 91 \\ 89 & 58 & 98 \\ 94 & 79 & 65 \end{pmatrix}$$

$$V^{(5,4)} = \begin{pmatrix} 92 & 78 & 93 \\ 92 & 55 & 89 \\ 91 & 60 & 45 \\ 89 & 52 & 86 \\ null & null & null \\ 95 & 65 & 95 \\ 92 & 59 & 95 \\ 86 & 73 & 65 \end{pmatrix} \quad V^{(6,4)} = \begin{pmatrix} 96 & 72 & 85 \\ 92 & 59 & 89 \\ 99 & 49 & 56 \\ 85 & 56 & 99 \\ 87 & 54 & 76 \\ null & null & null \\ 94 & 56 & 97 \\ 95 & 76 & 76 \end{pmatrix}$$

$$V^{(7,4)} = \begin{pmatrix} 95 & 78 & 100 \\ 89 & 57 & 99 \\ 86 & 56 & 52 \\ 93 & 55 & 96 \\ 94 & 58 & 72 \\ 87 & 74 & 90 \\ null & null & null \\ 89 & 67 & 79 \end{pmatrix} \quad V^{(8,4)} = \begin{pmatrix} 83 & 78 & 94 \\ 85 & 56 & 95 \\ 93 & 56 & 43 \\ 94 & 56 & 93 \\ 95 & 55 & 78 \\ 95 & 73 & 96 \\ 95 & 42 & 97 \\ null & null & null \end{pmatrix}$$

C4. Collective preference and consensus degree.

In round 1, the collective preference is,

$$P^{(c,1)} = \begin{pmatrix} 0.5 & 0.5375 & 0.5013 & 0.5901 & 0.5294 & 0.6386 \\ 0.4625 & 0.5 & 0.5661 & 0.5710 & 0.6128 & 0.6741 \\ 0.4987 & 0.4339 & 0.5 & 0.6853 & 0.6037 & 0.6635 \\ 0.4099 & 0.4290 & 0.3147 & 0.5 & 0.5637 & 0.5940 \\ 0.4706 & 0.3872 & 0.3963 & 0.4363 & 0.5 & 0.6820 \\ 0.3614 & 0.3259 & 0.3365 & 0.4060 & 0.3168 & 0.5 \end{pmatrix}$$

.

The non-cooperative behavior matrix is,

$$NC^{(1)} = \begin{pmatrix} 0&0&0 \\ 0&0&0 \\ 0&0&0 \\ 0&0&0 \\ 0&0&0 \\ 0&0&0 \\ 0&0&0 \\ 0&0&0 \end{pmatrix}$$

The consensus level reaches $cl^1 = 0.7284$

In round 2, the collective preference matrix is,

$$P^{(c,2)} = \begin{pmatrix} 0.5 & 0.5375 & 0.5013 & 0.5901 & 0.5294 & 0.6386 \\ 0.4625 & 0.5 & 0.5661 & 0.5710 & 0.6128 & 0.6741 \\ 0.4987 & 0.4339 & 0.5 & 0.6853 & 0.6037 & 0.6635 \\ 0.4099 & 0.4290 & 0.3147 & 0.5 & 0.5637 & 0.5940 \\ 0.4706 & 0.3872 & 0.3963 & 0.4363 & 0.5 & 0.6820 \\ 0.3614 & 0.3259 & 0.3365 & 0.4060 & 0.3168 & 0.5 \end{pmatrix}$$

The non-cooperative matrix is,

$$NC^{(2)} = \begin{pmatrix} 0&0&0 \\ 0&0&0 \\ 0&0&0 \\ 0&0&0 \\ 0&0&0 \\ 0&0&0 \\ 0&0&0 \\ 0&0&0 \end{pmatrix}$$

The consensus degree reaches $cl^2 = 0.7721$.

In round 3, the collective preference matrix is,

$$P^{(c,3)} = \begin{pmatrix} 0.5 & 0.5253 & 0.5038 & 0.6253 & 0.5176 & 0.6471 \\ 0.4747 & 0.5 & 0.5912 & 0.5663 & 0.5918 & 0.6773 \\ 0.4962 & 0.4088 & 0.5 & 0.6822 & 0.5593 & 0.7215 \\ 0.3747 & 0.4337 & 0.3178 & 0.5 & 0.5772 & 0.6355 \\ 0.4824 & 0.4082 & 0.4407 & 0.4228 & 0.5 & 0.6702 \\ 0.3529 & 0.3227 & 0.2785 & 0.3645 & 0.3298 & 0.5 \end{pmatrix}$$

The non-cooperative matrix is,

$$NC^{(3)} = \begin{pmatrix} 1&0&0 \\ 1&0&0 \\ 1&1&0 \\ 1&0&0 \\ 1&0&0 \\ 1&1&0 \\ 1&0&0 \\ 1&1&0 \end{pmatrix}$$

The consensus degree reaches $cl^3 = 0.8287$.

In round 4, the collective preference matrix is,

$$P^{(c,4)} = \begin{pmatrix} 0.5 & 0.5585 & 0.4427 & 0.6522 & 0.5122 & 0.5779 \\ 0.4415 & 0.5 & 0.5952 & 0.5346 & 0.5674 & 0.7176 \\ 0.5573 & 0.4048 & 0.5 & 0.6995 & 0.5818 & 0.6833 \\ 0.3478 & 0.4654 & 0.3005 & 0.5 & 0.5663 & 0.5991 \\ 0.4878 & 0.4326 & 0.4182 & 0.4337 & 0.5 & 0.6655 \\ 0.4221 & 0.2824 & 0.3167 & 0.4009 & 0.3345 & 0.5 \end{pmatrix}$$

The non-cooperative behavior matrix is,

$$NC^{(4)} = \begin{pmatrix} 0&0&0 \\ 1&0&0 \\ 1&1&0 \\ 1&0&0 \\ 1&0&0 \\ 0&0&0 \\ 1&0&0 \\ 0&0&0 \end{pmatrix}$$

The consensus level reaches $cl^4 = 0.8517$.

Appendix D: The OWA operator applied in the current work

Definition 3 *[48] Suppose that $\{c_1, c_2, \ldots, c_N\}$ is a set of values to be aggregated, the OWA operator is defined by*

$$OWA(c_1, c_2, \ldots, c_N) = \sum_{z=1}^{N} \pi_z b_z \tag{D1}$$

b_k is the value of the z-th largest of $\{c_1, c_2, \ldots, c_N\}$, $\pi = (\pi_1, \pi_2, \ldots, \pi_N)^T$ is a weight vector, $\pi_z \in (0, 1)$ and $\sum_{z=1}^{N} \pi_z = 1$.

In [33, 34], $\pi = (\pi_1, \pi_2, \ldots, \pi_N)^T$ can be obtained by linguistic quantifier as below.

$$\pi_z = Q\left(\frac{z}{N}\right) - Q\left(\frac{z-1}{N}\right) \tag{D2}$$

$$Q(z) = \begin{cases} 0 & z < a \\ \frac{z-a}{b-a}, & a < z < b, a, b, z \in (0, 1] \\ 1, & z > b \end{cases} \quad \text{(D3)}$$

with parameters $a = 0.5$ and $b = 1$.

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Data availability and access The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials.

Declarations

Competing interests 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.

Ethics approval Since the data used for this research does not involve human or animal participants, this section is not applicable.

References

1. Kacprzyk J (1986) Group decision making with a fuzzy linguistic majority. Fuzzy Sets Syst 18(2):105–118
2. Garcia-Zamora D, Labella A, Ding WP, Rodríguez RM, Martínez L (2022) Large-scale group decision making: A systematic review and a critical analysis. IEEE/CAA J Autom Sin 9:949–966
3. Hochbaum DS, Levin A (2006) Methodologies and algorithms for group-rankings decision. Manag Sci 52:1394–1408
4. Martínez L (2007) Montero J Challenges for improving consensus reaching process in collective decisions. New Math Nat Comput 03:203–217
5. Bezdek JC, Spillman B, Spillman RJ (1978) A fuzzy relation space for group decision theory. Fuzzy Sets Syst 1:255–268
6. Herrera-Viedma E, Cabrerizo FJ, Kacprzyk J, Pedrycz W (2014) A review of soft consensus models in a fuzzy environment. Inf Fusion 17:4–13
7. Zhang Z, Li Z (2022) Personalized individual semantics-based consistency control and consensus reaching in linguistic group decision making. IEEE Trans Syst Man Cybern: Syst 52(9):5623–5635
8. Li P, Xu Z, Zhang Z, Li Z, Wei C (2023) Consensus reaching in multi-criteria social network group decision making: A stochastic multicriteria acceptability analysis-based method. Inf Fusion 97:101825
9. Dong Y, Zha Q, Zhang H, Herrera F (2021) Consensus reaching and strategic manipulation in group decision making with trust relationships. IEEE Trans Syst Man Cybern: Syst 51(10):6304–6318
10. Quesada FJ, Palomares I, Martínez L (2015) Managing experts behavior in large-scale consensus reaching processes with uninorm aggregation operators. Appl Soft Comput 35:873–887
11. Gou X, Xu Z (2021) Managing noncooperative behaviors in large-scale group decision-making with linguistic preference orderings: The application in internet venture capital. Inf Fusion 69:142–155
12. Palomares I, Martínez L, Herrera F (2014) A consensus model to detect and manage noncooperative behaviors in large-scale group decision making. IEEE Trans Fuzzy Syst 22(3):516–530
13. Xue M, Fu C, Yang S (2020) Group consensus reaching based on a combination of expert weight and expert reliability. Appl Math Comput 369:124902
14. Du Z, Yu S, Xu X (2020) Managing noncooperative behaviors in large-scale group decision-making: Integration of independent and supervised consensus-reaching models. Inf Sci 531(4):119–138
15. Mandal P, Samanta S, Pal M (2022) Large-scale group decision-making based on pythagorean linguistic preference relations using experts clustering and consensus measure with non-cooperative behavior analysis of clusters. Complex Intell Syst 8:819–833
16. Dong Y, Zhang H, Herrera-Viedma E (2016) Integrating experts' weights generated dynamically into the consensus reaching process and its applications in managing non-cooperative behaviors. Decis Support Syst 84:1–15
17. Dong Y, Zhao S, Zhang H, Chiclana F, Herrera-Viedma E (2018) A self-management mechanism for noncooperative behaviors in large-scale group consensus reaching processes. IEEE Trans Fuzzy Syst 26(6):3276–3288
18. Liu B, Guo S, Yan K, Li L, Wang X (2021) A consensus model to manage the non-cooperative behaviors of individuals in uncertain group decision making problems during the covid-19 outbreak. Appl Soft Comput 99(1):106879
19. Xu X, Du Z, Chen X (2015) Consensus model for multi-criteria large-group emergency decision making considering non-cooperative behaviors and minority opinions. Decis Support Syst 79:150–160
20. Tian Z, Nie R, Wang J (2019) Social network analysis-based consensus-supporting framework for large-scale group decision-making with incomplete interval type-2 fuzzy information. Inf Sci 502:446–4714
21. Zadeh LA (1965) Fuzzy sets. Inf Control 8:338–353
22. Orlovsky SA (1978) Decision-making with a fuzzy preference relation. Fuzzy Sets Syst 1:155–167
23. Palomares I, Estrella FJ, Martínez L, Herrera F (2014) Consensus under a fuzzy context: Taxonomy, analysis framework afryca and experimental case of study. Inf Fusion 20(11):252–271
24. Calvo T, De Baets B, Fodor J (2001) The functional equations of frank and alsina for uninorms and nullnorms. Fuzzy Sets Syst 120(3):385–394
25. Campos Souza PV, Lughofer ED (2022) An advanced interpretable fuzzy neural network model based on uni-nullneuron constructed from n-uninorms. Fuzzy Sets Syst 426:1–26
26. Calvo T, Baets BD, Fodor JC (2001) The functional equations of frank and alsina for uninorms and nullnorms. Fuzzy Sets Syst 120:385–394
27. Xu X, Zhang Q, Chen X (2020) Consensus-based non-cooperative behaviors management in large-group emergency decision-making considering experts' trust relations and preference risks. Knowl-based Syst 190:105108
28. Gou X, Xu Z (2021) Managing noncooperative behaviors in large-scale group decision-making with linguistic preference orderings: The application in internet venture capital. Inf Fusion 69:142–155
29. Shi Z, Wang X, Palomares I, Guo S, Ding R (2018) A novel consensus model for multi-attribute large-scale group decision making based on comprehensive behavior classification and adaptive weight updating. Knowl-based Syst 158:196–208

30. Xiong K, Dong Y, Zha Q (2023) A large-scale consensus model to manage non-cooperative behaviors in group decision making: A perspective based on historical data. Expert Syst Appl 214:119163
31. Palomares I, Martínez-López L, Herrera F (2014) A consensus model to detect and manage noncooperative behaviors in large-scale group decision making. IEEE Trans Fuzzy Syst 22:516–530
32. Herrera-Viedma E, Herrera F, Chiclana F (2002) A consensus model for multiperson decision making with different preference structures. IEEE Trans Syst Man Cybern A Syst Hum 32(3):394–402
33. Yager RR (1996) Quantifier guided aggregation using owa operators. Int J Intell Syst 11(1):49–73
34. Wu J, Li X, Chiclana F, Yager R (2019) An attitudinal trust recommendation mechanism to balance consensus and harmony in group decision making. IEEE Trans Fuzzy Syst 27(11):2163–2175
35. Hwang CL, Yoon K (1979) Multiple attribute decision making : methods and applications : a state-of-the-art survey
36. Filev D, Yager RR (1998) On the issue of obtaining owa operator weights. Fuzzy Sets Syst 94:157–169
37. Liu H, Rodríguez RM (2014) A fuzzy envelope for hesitant fuzzy linguistic term set and its application to multicriteria decision making. Inf Sci 258:220–238
38. Labella Á, Liu Y, Rodríguez RM, Martínez L (2018) Analyzing the performance of classical consensus models in large scale group decision making: A comparative study. Appl Soft Comput 67:677–690
39. Gao Y, Zhang Z (2022) Consensus reaching with non-cooperative behavior management for personalized individual semantics-based social network group decision making. J Oper Res Soc 73(11):2518–2535
40. Quesada F, Palomares I, Martínez L (2015) Managing experts behavior in large-scale consensus reaching processes with uninorm aggregation operators. Appl Soft Comput 35:873–887
41. Xu X, Du Z, Chen X (2015) Consensus model for multi-criteria large-group emergency decision making considering non-cooperative behaviors and minority opinions. Decis Support Syst 79:150–160
42. Xu X, Du Z, Chen X, Cai C (2019) Confidence consensus-based model for large-scale group decision making: A novel approach to managing non-cooperative behaviors. Inf Sci 477:410–427
43. Mandal Prasenjit SS, Madhumangal P (2021) Large-scale group decision-making based on pythagorean linguistic preference relations using experts clustering and consensus measure with non-cooperative behavior analysis of clusters. Complex Intell Syst 8:819–833
44. Xiang L (2020) Energy emergency supply chain collaboration optimization with group consensus through reinforcement learning considering non-cooperative behaviours. Energy 210:118597
45. Xu W, Chen X, Dong Y, Chiclana F (2021) Impact of decision rules and non-cooperative behaviors on minimum consensus cost in group decision making. Group Decis Negot 30(6):1239–1260
46. Li C-C, Dong Y, Xu Y, Chiclana F, Herrera-Viedma E, Herrera F (2019) An overview on managing additive consistency of reciprocal preference relations for consistency-driven decision making and fusion: Taxonomy and future directions. Inf Fusion 52:143–156
47. García-Zamora D, Labella A, Ding W, Rodriguez RM, Martínez L (2022) Large-scale group decision making: A systematic review and a critical analysis. IEEE/CAA J Autom Sin 9:949–966
48. Yager RR (1988) On ordered weighted averaging aggregation operators in multicriteria decisionmaking. IEEE Trans Syst Man Cybern 18(1):183–190

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