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The maximum effort consensus model considering the emotions of decision-makers in the social network environment

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Abstract: In language social network group decision-making, social network analysis often helps determine the importance weights of decision-makers. In fact, decision-maker emotions can have an impact on the spread of trust among decision-makers. For example, positive emotions can enhance trust, while negative emotions can suppress it. Therefore, this paper constructs a social network trust propagation mechanism that takes into account the emotions of decision-makers. Secondly, in the process of reaching consensus, managers often need to modify their opinions, and the probability of decision-makers' adjustment based on emotion is defined simultaneously. Also, the willingness and attitude of decision-makers to modify for a better consensus, that is, the degree of effort, can lead to different consensus outcomes. In the case of limited cost budgets, we propose a maximum effort consensus model driven by the maximization of decision-makers' efforts to advise individuals. Finally, the model approach proposed in this paper was applied to the case of brand selection of green wall insulation materials and compared with the consensus results guided by the identity-optimization rule method to verify the rationality and superiority of the method proposed in this paper.

Keywords: Social network; Personalized semantics; Decision-maker sentiment; Degree of effort

1. Introduction

Group Decision-Making[1-5] (GDM) aims to find a collective solution to a decision-making problem based on the preferences (or opinions) expressed by a group of decision-makers (or individuals). In general, the preferences of decision-makers can vary greatly because they come from different fields, knowledge backgrounds and interests, especially in the current era of social networks, where the rapid expansion of information has exacerbated such differences. However, in actual decision-making, it is crucial to form a consensus on a collective solution that can be approved by the vast majority of decision-makers, and the consensus is an important indicator of the success of the decision. Therefore, a Consensus Reaching Process (CRP) is introduced in group decision-making to help decision-makers reach a consistent collective solution[6-8]. On the one hand, the consensus-reaching process promotes interaction among decision-makers to build closer interpersonal relationships, thereby reducing differences in preferences among them; On the other hand, the solutions formed through this process can be more focused on the needs of decision-makers, thereby enhancing the execution of the solutions[9].

In general, decision-makers adjust their preferences under the influence of feedback mechanisms until they reach a consensus. In existing studies, preference modifications are often driven by two types of feedback mechanisms: (1) Identifications-direction rules are used to identify decision-makers with poor consensus, alternatives, and preference values and provide directions for preference correction to facilitate group consensus [11-13]; (2) The optimization rules are designed to pursue the minimum cost or preference adjustment. In fact, preference adjustments almost always require multiple rounds of discussion, which leads to an increase in cost during the consensus process, and in most cases in real decision-making, resources are limited in various ways, Liu et al. proposed the minimum adjustment consensus model and defined the minimum cost consensus model[14]. Dong et al. established the connection between the minimum adjustment consensus model and the minimum cost consensus model, and proposed a new minimum cost consensus achievement framework based on the assembly function[15].

2. Problem Description and methodological Basis

2.1 Decision-making problem description

Group decision-making involves multiple decision-making individuals discussing together. Besides judging based on individual skills and knowledge, individuals tend to refer to the opinions of other highly skilled and prestigious decision-makers within the group. The mutual trust among the decision-makers constitutes the social network relationship within the group. The different emotional states of decision-makers also affect the degree of trust among them, and the probability of decision-making individuals under different emotions being willing to adjust their opinions also varies. In general, the realization of consensus requires a long process of discussion and is accompanied by a limited individual compensation budget. How to encourage decision-makers to do their best to contribute to the consensus under the condition of meeting the given cost, thereby improving decision-making efficiency and obtaining decision-making results that are unanimously satisfactory to the group is the core issue of this study.

$D = \{d_1, d_2, \dots, d_m\}$ It is a collection of experts with different specialties, skills and backgrounds, and with varying degrees of trust among them. Now evaluate a set of alternatives for the cost required to adjust the unit evaluation opinion for the experts, for the weight of the experts' importance, and for the minimum consensus level that should be met. $X = \{x_1, x_2, \dots, x_n\}$ $C = \{c_1, c_2, \dots, c_m\}$ $W = \{w_1, w_2, \dots, w_m\}$ $\sum_{i=k}^{m} w_k = 1$ ε Given a set of language terms, experts make language evaluations of each option in sequence based on the decision-making problem and available information. $S=\{s_1,s_2,\ldots,s_g\}$ Considering the impact of different expert emotional states on the consensus process, each expert is adjusted to the greatest extent possible in the direction of improving the consensus at a given budget cost, and ultimately the best option is determined. Ω

2.2 Binary Semantics and Numerical Scaling

Let it be a set of language terms, where, is the granularity of the set of language terms, satisfies the following two conditions $S=\{s_0,s_1,\ldots,s_g\}$:

(1) orderliness: if; $i \le j$, 则 $s_i \le s_j$

(2) Negative operator:. $Neg(s_i)=s_{g-i}$

Definition 1[16] Let the set of language terms be the symbolic aggregation operator, representing the real number obtained by some aggregation operation of the language terms, then the equivalent transformation with the semantic information of the tuple is denoted as $S=\{s_0,s_1,\ldots,s_g\}$.

$$\Delta:[0,g]\rightarrow S\times[-0.5,0.5)$$
$$\Delta(\beta)=(s_i,\alpha),\ 且\begin{cases} s_i, i=\text{round}(\beta), \\ \alpha=\beta-i, \alpha\in[-0.5,0.5) \end{cases} \tag{1}$$

Where round is the rounding operator and is the sign transfer value, representing the difference between the language term and the result of the aggregation operation. α s_i β The corresponding inverse operation can be denoted as $\Delta^{-1}(\beta)$

$$\Delta^{-1}:S\times[-0.5,0.5)\rightarrow[0,g]$$
$$\Delta^{-1}(s_i,\alpha)=i+\alpha=\beta \tag{2}$$

Obviously, particularly. $\text{Neg}((s_i,\alpha))=\Delta(g-(\Delta^{-1}(s_i,\alpha)))$ $\text{Neg}(s_i)=s_{g-i}$

Definition 2[17] Let the set of language terms be the set of real numbers, and define a function that is about the scale function, known as the numerical scale of the language terms. $S=\{s_0,s_1,\ldots,s_g\}$ R $NS:S\rightarrow R$ S $NS(s_i)$ s_i If arbitrary, that is, ordered, it can be expressed as $i=0,1,\ldots,g-1,\ NS(s_{i+1})>NS(s_i)$ NS $NS(s_i,\alpha)$

$$NS(s_i,\alpha)=\begin{cases} NS(s_i)+\alpha\times(NS(s_{i+1})-NS(s_i) & \alpha\ge 0 \\ NS(s_i)+\alpha\times(NS(s_i)-NS(s_{i-1}) & \alpha<0 \end{cases} \tag{3}$$

The corresponding inverse operation is

$$NS^{-1}:R\rightarrow S\times[-0.5,0.5)$$
$$NS^{-1}(r)=\begin{cases} \left(s_i,\dfrac{r-NS(s_i)}{NS(s_{i+1})-NS(s_i)}\right) & NS(s_i)<r<\dfrac{NS(s_i)+NS(s_{i+1})}{2} \\ \left(s_{i+1},\dfrac{r-NS(s_{i+1})}{NS(s_{i+1})-NS(s_i)}\right) & \dfrac{NS(s_i)+NS(s_{i+1})}{2}\le r\le NS(s_{i+1}) \end{cases} \tag{4}$$

2.3 Consensus Measurement

Remember individual language preference evaluations, which can be transformed into individual fuzzy preference evaluations based on different semantic understandings of decision-makers. $L^k=(l_j^k)_{1\times n}$ $F^k=(f_j^k)_{1\times n}$ Then, by adding the weighted average of individual fuzzy preference evaluations, a collective fuzzy relation preference matrix is obtained, where $\overline{F} = (\overline{f}_{ij})_{n\times n}$

$$\overline{f}_j = \sum_{k=1}^{m}(w_k \times f_j^k) \tag{5}$$

$W = \{w_k \mid k = 1,2,\ldots,m\}$ Is the weight of the importance of the decision-making individual, and. $\sum_{k=1}^{m} w_k = 1$

Definition 3[18] According to the individual and collective fuzzy preference relation matrix, the individual consensus level and the collective consensus level can be expressed as CL^k CL

$$CL^k = 1 - \frac{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}\left|f_{ij}^k - \overline{f}_{ij}\right|}{n(n-1)} \tag{6}$$

$$CL = \sum_{k=1}^{m}(w_k \times CL^k) \tag{7}$$

Obviously, the larger the collective consensus level value, the more the decision-making individuals recognize each other and the higher the degree of consensus. CL If the value is less than the established consensus threshold, further adjustments are needed to increase the overall consensus level. CL ε

If the consensus level is acceptable to all individuals, the collective evaluation ranking value of the scheme is denoted as $x_i (i = 1,2,\ldots,n)$

$$\overline{f}_i = \frac{1}{n}\sum_{j=1}^{n}\overline{f}_{ij}, \quad j = 1,2,\ldots,n \tag{8}$$

The size of the comparison gives the ranking of the corresponding scheme. $\overline{f}_i$

2.4 Consensus Improvements

The decision-making process is often repetitive, and multiple feedback correction processes are required to ensure ultimately satisfactory consensus, mainly including the following two consensus improvement rules:

(1) The identity-direction rule

Identification rules are designed to determine the decision-making individuals whose preference evaluation information needs to be modified, typically set as decision-making individuals whose individual consensus level is below the preset threshold, that is. ε $D_I = \{d_u \mid CL^u < \varepsilon, u = 1,2,\ldots,m\}$

The direction rule aims to determine the direction and extent of the correction of individual preference information for the decision to be adjusted. Given the readability of language preferences, the collective fuzzy relation preference matrix can be transformed into an individual language preference relation with individualized understanding according to Equation (2.4), where the decision-making individual can adjust the preference with reference to the collective language preference evaluation information, see Table 1. $\overline{F} = (\overline{f}_{ij})_{n\times n}$ $\overline{L}^u = (\overline{l}_{ij}^u)_{n\times n}$ $\overline{l}_{ij}^u = NS^{u,-1}(\overline{f}_{ij})$

Table 1 Direction Rules

(2) Optimization rules

Optimization rules are designed to construct mathematical programming models pursued by corresponding feature objectives, such as total cost, total adjustment, and the optimal solution of the model ensures that the established consensus requirements can be directly met. A common minimum cost consensus model (MCCM)[7] is designed as follows

$$\min \sum_{k=1}^{m} c_k \cdot |o'_k - o_k|$$
$$s.t.\begin{cases} \overline{o}' = \sum_{k=1}^{m} w_k o'_k \\ |o'_k - \overline{o}'| \le \delta \qquad , \qquad k = 1, 2, \dots, m \\ CL \ge \varepsilon \end{cases} \tag{9}$$

Here represents the unit preference modification cost of the decision-making individual, referring respectively to the preference opinions of the decision-making individual before and after modification, referring to the collective preference opinion after modification, which is the maximum acceptable adjustment range between the individual and collective preference opinions. c_k d_k o_k和o'_k d_k $\overline{o}'$ δ

Table 1. Preference representation structures of the k-th DM

Use conditions	Adjust Strategy	Reference range
$l_{ij}^u < \overline{l}_{ij}^u$	Increase the preference of the i-th option over the j-th option	$(l_{ij}^u, \overline{l}_{ij}^u]$
$l_{ij}^u = \overline{l}_{ij}^u$	No change	——
$l_{ij}^u > \overline{l}_{ij}^u$	Reduce the degree of preference for the i-th option over the j-th option	$[\overline{l}_{ij}^u, l_{ij}^u)$

2.5 Social Networks and Trust Propagation

The interconnections and interactions of people in a social environment can be expressed as rules and patterns based on relationships, while social network analysis[19-21] focuses on the relationships among members of social groups. Social networks generally consist of three elements: participants, the relationships among participants, and the attribute data of interactions, which can be characterized by adjacency matrices, network relationship diagrams, and algebraic forms, as shown in Table 2.

(1) Adjacency matrix: An adjacency matrix composed of 0s and 1s is used to represent information about social relationships among participants. If the participants trust the participants directly, the element value at the corresponding position in the matrix is 1; otherwise, it is 0. d_i d_j

(2) Network relationship diagram: It depicts the relationships among all participants by a set of nodes and directed edges. Nodes represent each participant, and when participants trust each other directly, an edge to which a node points can be determined. d_i d_j d_i d_j

(3) Algebraic form: Record the interactions among participants through algebraic expressions. If the participants trust each other directly, it is denoted as. d_i d_j $d_i R d_j$

However, there are not all direct connections among the participants in a social group, and indirect influence relationships cannot be ignored either. Therefore, in order to obtain the complete social network relationship, the trust propagation method based on operators $t-norm$ is proposed to infer the indirect trust relationship.

Define 2.7. let be the trust path passed from participant to participant, be the path length, then the trust value of any pair can be derived as $d_k \xrightarrow{1} d_{\sigma(1)} \xrightarrow{2} d_{\sigma(2)} \xrightarrow{3} \cdots \xrightarrow{v} d_{\sigma(v)} \xrightarrow{v+1} d_h$ d_k d_h $v+1$ d_k d_h tv_{kh}

$$tv_{kh} = \frac{2tv_{k,\sigma(1)} \cdot tv_{\sigma(\varsigma),h} \prod_{\varsigma=1}^{v-1} tv_{\sigma(\varsigma),\sigma(\varsigma+1)}}{(2-tv_{k,\sigma(1)})(2-tv_{\sigma(v),h}) \prod_{\varsigma=1}^{v-1}(2-tv_{\sigma(\varsigma),\sigma(\varsigma+1)}) + tv_{k,\sigma(1)} \cdot tv_{\sigma(v),h} \prod_{\varsigma=1}^{v-1} tv_{\sigma(\varsigma),\sigma(\varsigma+1)}} \tag{10}$$

When there is a trust path between two participants, the final trust value can be aggregated and represented as $N(N \geq 2)$

$$tv_{kh} = OWA(tv_{kh}^1, tv_{kh}^2, \ldots, tv_{kh}^N) = \sum_{ƛ=1}^{N} \pi_ƛ \cdot tv_{kh}^{\sigma(ƛ)} \tag{11}$$

Here is the largest value, which is the path weight $tv_{kh}^{\sigma(ƛ)}$ $\{tv_{kh}^1, tv_{kh}^2, \ldots, tv_{kh}^N\}$ $ƛ$ $\pi_ƛ$ [90] calculated by the language quantifier.

$$\pi_ƛ = Q\left(\frac{ƛ}{N}\right) - Q\left(\frac{ƛ-1}{N}\right),\quad ƛ = 1,2,\ldots,N$$

$$Q(a) = \begin{cases} 0 & a < y \\ \dfrac{a-y}{Υ-y} & y \leq a \leq Υ, \qquad 其中a, y和Υ \in [0,1] \\ 1 & a > Υ \end{cases} \tag{12}$$

The range of mapping varies among different language quantifiers. Here, let the upper and lower bound values corresponding to the language quantifier "most" be 0.3 and 0.8, that is. $(y,\ Υ)$ $(y,\ Υ) = (0.3,\ 0.8)$

Table 2. Representation of Social Networks

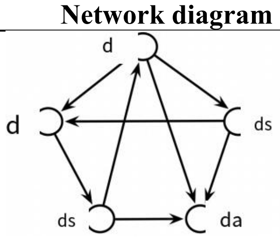
Adjacency matrix	**Network diagram**	**Algebraic form**
$\begin{pmatrix} 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 \end{pmatrix}$		d_1Rd_2 d_3Rd_1 d_1Rd_4 d_3Rd_4 d_1Rd_5 d_4Rd_5 d_2Rd_3 d_5Rd_2

Table 3. Summary of General Group Consensus Decision Models Based on Optimization Rules

References	**Model Types**	**Target content**	**Decision variables**	**Consensus constraints**	**Preference aggregation**
[6]	Minimum adjustment consensus decision model	Total preference adjustment magnitude	Adjusted preferences	is	is
[8]	Minimum cost consensus decision model	Total opinion modification cost	Adjusted preferences	no	no
[8]	Minimum cost consensus optimization decision model	Total opinion modification cost	Adjusted preference	is	is

3. A maximum effort consensus model based on decision-maker sentiment

3.1 Social trust networks considering emotions

Interactions among participants in social network groups mainly consider the influence of trust, prestige, conformity, etc., while different emotional states of individuals also have an effect on mutual trust. For example, when the emotional state of the trusted decision-making individual is better, the trust of other decision-making individuals in that individual will also increase. Therefore, the following study introduces the emotions of decision-making individuals into the conventional social network analysis to further obtain more accurate trust relationships.

Definition 4.1 Let a set of positively increasing emotional states be the probabilistic assessment of the decision-making individual's current emotional state, then the distributed emotional assessment is denoted as $\{emo^1, emo^2, \dots, emo^K\}, (K \geq 2)$ $\varphi_{kh}^{\kappa} (\varphi_{kh}^{\kappa} \geq 0)$ d_k d_h EMO_{kh}

$$EMO_{kh} = \{(emo^{\kappa}, \varphi_{kh}^{\kappa}) \mid \kappa = 1, 2, \dots, K;\ k, h = 1, 2, \dots, m \text{ 且 } k \neq h\} \tag{13}$$

Let the sentiment assessment be a numerical mapping and strictly monotonically increasing, then the comprehensive sentiment assessment value of the decision-making individual to the decision-making individual can be expressed as $\psi(emo^{\kappa})$ $emo^{\kappa}, (\kappa = 1, 2, \dots, K)$ d_k d_h $Exp(EMO_{kh})$

$$Exp(EMO_{kh}) = \sum_{\kappa=1}^{K} [\psi(emo^{\kappa}) \times \varphi_{kh}^{\kappa}] \tag{14}$$

Definition 4.2 Let the binary relationship information between decision-makers be, then the distributed trust-sentiment adjacency matrix be d_k d_h (tv_{kh}, EMO_{kh}) DTE

$$\begin{bmatrix}
- & \left(tv_{12}, \begin{Bmatrix} (emo_{12}^1, \varphi_{12}^1) \\ (emo_{12}^2, \varphi_{12}^2) \\ \vdots \\ (emo_{12}^K, \varphi_{12}^K) \end{Bmatrix}\right) & \cdots & \left(tv_{1m}, \begin{Bmatrix} (emo_{1m}^1, \varphi_{1m}^1) \\ (emo_{1m}^2, \varphi_{1m}^2) \\ \vdots \\ (emo_{1m}^K, \varphi_{1m}^K) \end{Bmatrix}\right) \\
\left(tv_{21}, \begin{Bmatrix} (emo_{21}^1, \varphi_{21}^1) \\ (emo_{21}^2, \varphi_{21}^2) \\ \vdots \\ (emo_{21}^K, \varphi_{21}^K) \end{Bmatrix}\right) & - & \cdots & \left(tv_{2m}, \begin{Bmatrix} (emo_{2m}^1, \varphi_{2m}^1) \\ (emo_{2m}^2, \varphi_{2m}^2) \\ \vdots \\ (emo_{2m}^K, \varphi_{2m}^K) \end{Bmatrix}\right) \\
\vdots & \vdots & \ddots & \vdots \\
\left(tv_{m1}, \begin{Bmatrix} (emo_{m1}^1, \varphi_{m1}^1) \\ (emo_{m1}^2, \varphi_{m1}^2) \\ \vdots \\ (emo_{m1}^K, \varphi_{m1}^K) \end{Bmatrix}\right) & \cdots & \left(tv_{mm-1}, \begin{Bmatrix} (emo_{mm-1}^1, \varphi_{mm-1}^1) \\ (emo_{mm-1}^2, \varphi_{mm-1}^2) \\ \vdots \\ (emo_{mm-1}^K, \varphi_{mm-1}^K) \end{Bmatrix}\right) & -
\end{bmatrix}$$

(4.3)

Based on Equation (4.2), the above matrix can be further simplified to a trust-sentiment adjacency matrix as follows TE

$$TE = \begin{bmatrix}
- & (tv_{12}, Exp(EMO_{12})) & \cdots & (tv_{1m}, Exp(EMO_{1m})) \\
(tv_{21}, Exp(EMO_{21})) & - & \cdots & (tv_{2m}, Exp(EMO_{2m})) \\
\vdots & \vdots & \ddots & \vdots \\
(tv_{m1}, Exp(EMO_{m1})) & \cdots & (tv_{mm-1}, Exp(EMO_{mm-1})) & -
\end{bmatrix}$$

(15)

The comprehensive sentiment assessment value of the non-directly acting decision-making individual is calculated in the same way as the indirect trust defined in 2.7 is the trust-sentiment adjacency matrix with complete information. $TE = (te_{kh})_{m \times m}$, 其中 $te_{kh} = (tv_{kh}, Exp(EMO_{kh}))$

Definition 4.3 Let the in-degree center index of the decision-maker gaining the trust of others be d_h $C(d_h)$

$$C(d_h) = \frac{1}{m-1}\sum_{k=1,h\neq k}^{m}\left[tv_{kh}\cdot Exp(EMO_{kh})\right] \tag{16}$$

$C(d_h)$ The higher the value, the greater the influence of the decision-maker in the social network group. d_h Therefore, the weight of the decision-maker's importance can be expressed as d_h

$$w_h = \frac{C(d_h)}{\sum_{k=1}^{m} C(d_k)} \tag{17}$$

3.2 Maximum Effort Consensus Model

In the decision-making process, individuals are often asked to try their best to adjust their preferences in order to please the majority of the group, and decision-making individuals with more positive emotional states are more likely to make positive adjustments. This chapter defines the willingness and attitude of decision-making individuals to adjust in order to reach a better consensus as individual effort.

Definition 4.4 is the probability that a decision-making individual is willing to make adjustments, then ϖ_k d_k

$$\varpi_k = \frac{\sum_{h=1,h\neq k}^{m} Exp(EMO_{hk}) - \min_{\iota=1}^{m}\sum_{h,\iota=1,h\neq\iota}^{m} Exp(EMO_{h\iota})}{\max_{\iota=1}^{m}\sum_{h=1,h\neq\iota}^{m} Exp(EMO_{h\iota}) - \min_{\iota=1}^{m}\sum_{h,\iota=1,h\neq\iota}^{m} Exp(EMO_{h\iota})} \tag{18}$$

Obviously, at that time, that is, it meant that the emotional state of the decision-making individual was relatively the worst, and it could be considered that they would not make any changes at all. $\sum_{h=1,h\neq k}^{m} Exp(EMO_{hk}) = \min_{\iota=1}^{m}\sum_{h,\iota=1,h\neq\iota}^{m} Exp(EMO_{h\iota})$ $\varpi_k = 0$ d_k And when, immediately, indicates that the decision-making individual's emotional state is relatively best, it can be assumed that they are completely willing to make a change. $\sum_{h=1,h\neq k}^{m} Exp(EMO_{hk}) = \max_{\iota=1}^{m}\sum_{h,\iota=1,h\neq\iota}^{m} Exp(EMO_{h\iota})$ $\varpi_k = 1$ d_k

Definition 4.5 Let the original and adjusted opinions of the decision-making individual be respectively, and the adjusted collective opinion be, then the effort of the decision-making individual be denoted as d_k o_k和o_k' $\overline{o}'$ d_k e_k

$$e_k = \operatorname{sgn}\left(|o_k - \overline{o}'| - |o_k' - \overline{o}'|\right)\cdot\frac{|\varpi_k\cdot o_k' - o_k|}{o_k} \tag{19}$$

$$\operatorname{sgn}\left(|o_k - \overline{o}'| - |o_k' - \overline{o}'|\right) = \begin{cases} -1, & |o_k - \overline{o}'| < |o_k' - \overline{o}'| \\ 0, & |o_k - \overline{o}'| = |o_k' - \overline{o}'| \\ 1, & |o_k - \overline{o}'| > |o_k' - \overline{o}'| \end{cases}$$

Here,.

(1) When, it indicates that the decision-making individual is making a reverse effort, going against the collective opinion, the distance between them and the collective opinion is widened, and they try to adjust their opinion in the opposite direction of the consensus; $|o_k - \overline{o}'| < |o_k' - \overline{o}'|$, $\operatorname{sgn}\left(|o_k - \overline{o}'| - |o_k' - \overline{o}'|\right) = -1$, $e_k < 0$ d_k

(2) At that time, it was indicated that the individual decision-makers did not make any changes to their original opinion, then they did not make an effort to reach the consensus, that is; $|o_k - \overline{o}'| = |o_k' - \overline{o}'|$, $o_k = o_k'$ d_k $e_k = 0$

(3) When, it indicates that the individual decision-makers are making positive efforts to reduce the distance between themselves and the collective opinion in order to advance the consensus. $|o_k-\bar{o}'|>|o_k'-\bar{o}'|,\ \mathrm{sgn}\left(|o_k-\bar{o}'|-|o_k'-\bar{o}'|\right)=1$, $e_k>0$ d_k

In addition, the positivity and absolute magnitude of the effort also reflect to some extent whether the decision-makers are inclined to cooperate and how they cooperate. For example, if the value is larger, it indicates that the decision-making individual is closer to the opinions of the majority and is more cooperative. $e_k>0\ and\ |e_k|\ d_k$

Definition 4.6 By summing up the weighted average of the effort of all decisions and their importance based on an emotional social network to summarize the effort of the group, the individual emotion-based maximum effort consensus model (MECM) driven by maximum effort is constructed as follows

$$\max\sum_{k=1}^{m} w_k e_k$$
$$s.t.\begin{cases} |o_k'-\bar{o}'|\le\delta, & (20-1)\\ \bar{o}'=\sum_{k=1}^{m} w_k o_k', & (20-2)\\ CL\ge\varepsilon, & (20-3)\\ \sum_{k=1}^{m} c_k\cdot|o_k'-o_k|\le\Omega, & (20-4)\\ o_k',\bar{o}'\ge 0,\ k=1,2,\dots,m. & (20-5)\end{cases} \tag{20}$$

Among them, is the known variable, is the compensation cost that the decision-making individual needs to obtain to adjust the unit preference opinion, and is the total budget cost that can be provided to achieve consensus. $\delta,w_k,o_k,\varepsilon,c_k$和$\Omega$ c_k d_k Ω The objective function is to maximize collective effort, that is, to make each decision-making individual work towards consensus as much as possible. The constraint (19-1) indicates the maximum acceptable deviation distance between the adjusted individual opinion and the collective opinion; δ Constraint (19-2) is a method of assembling collective opinions; Constraints (19-3) allow the lowest level of collective consensus to be met; Constraint (19-4) limits the total consensus cost not to exceed the limited budget. Ω

Given that the absolute value function contained in Equation (4.9) constraint is not easily solved directly, it can be further equivalently transformed into a standard nonlinear programming model as

$$\min\sum_{k=1}^{m} -\mathrm{sgn}\left(|o_k-\bar{o}'|-|o_k'-\bar{o}'|\right)\cdot\mathrm{sgn}(\varpi_k\cdot o_k'-o_k)\cdot w_k\times\frac{\varpi_k\cdot o_k'-o_k}{o_k}$$
$$s.t.\begin{cases} o_k'-\bar{o}'\le\delta & (21-1)\\ o_k'-\bar{o}'\ge-\delta & (21-2)\\ \bar{o}'=\sum_{k=1}^{m} w_k o_k' & (21-3)\\ CL\ge\varepsilon & (21-4)\\ \sum_{k=1}^{m} c_k\cdot\mathrm{sgn}(o_k'-o_k)(o_k'-o_k)\le\Omega & (21-5)\\ o_k',\bar{o}'\ge 0,\ k=1,2,\dots,m & (21-6)\end{cases} \tag{21}$$

3.3 Decision Framework

The main framework of the design content in this section is shown in Figure 1.

The specific decision-making steps are as follows:

(1) Social network analysis to determine expert weights

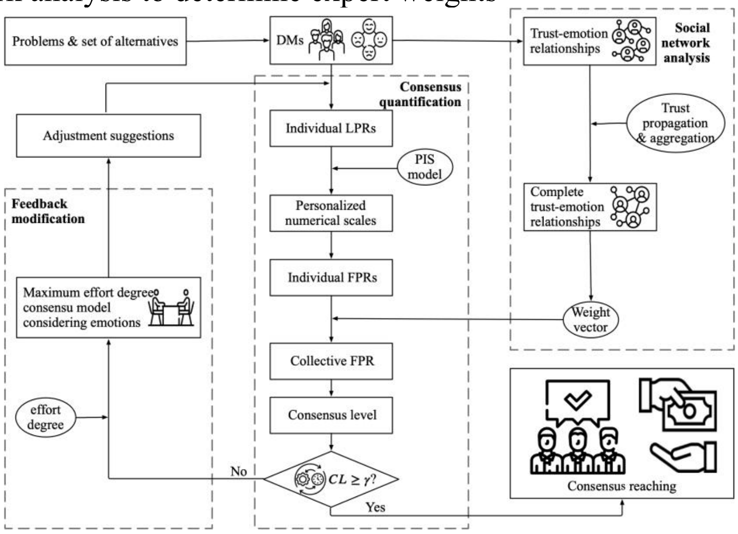


Figure 1. Maximum Effort Consensus Framework based on individual sentiment

Step 1: The decision-maker trust-sentiment network relationship is formed by evaluating each other's trust and sentiment among decision-making individuals, and on this basis, the calculation of indirect trust-sentiment path propagation is refined according to Definition 2.7 to form a complete trust-sentiment adjacency matrix. $TE = (te_{kh})_{m\times m}$

Step 2: Calculate the central index of the trust of the decision-making individual by other decision-makers based on Equation (15), and then determine the importance weight by obtaining the proportion of the degree of trust of the decision-making individual to the degree of trust of all decision-makers through equation (16). d_k $\{w_k\}_{k=1,2,\dots,5}$

Step 3: Consider the sentiment assessment values in the complete trust-sentiment adjacency matrix and determine the likelihood that the decision-making individual is willing to adjust the preference opinion according to Equation (17). $TE = (te_{kh})_{m\times m}$ $\varpi_k, k = 1,2,3,4,5$

(2) The consensus measurement phase

Step 1: Based on personalized semantic understanding, convert the individual language preference relation provided by the decision-making expert into an individual fuzzy preference relation with reference to the provided personalized individual semantic numerical scale for calculation. L^k F^k

Step 2: Combine the decision individual importance weights obtained in Step 2 of the social network analysis stage, and assemble the individual fuzzy preference relations of decision-makers into collective fuzzy preference relations through equation (8). $\overline{F}$

Step 3: Further obtain the individual consensus level and the collective consensus level based on equations (9) - (10), and compare the relationship between the collective consensus level and the consensus threshold. If not satisfied, proceed to the next stage; otherwise skip to the final scheme ranking stage. ε

(3) Consensus improvement phase - Based on the optimization of consensus rules

In connection with the decision individual adjustment probabilities obtained in the social network analysis stage, the effort level of the decision individual is obtained according to equation (16), and the known variable values are substituted into equation (17) for solving to obtain the best adjusted opinion of the decision individual for convenience as a correction suggestion for the reference of the decision individual, e_k F'^{k*} By converting the optimally adjusted fuzzy preference relation into the optimally adjusted language preference relation through equation (18), the language preference relation and the fuzzy preference relation after the re-adjustment of the decision individual are respectively denoted as and, calculate the compensation cost obtained by the decision individual and the total cost required for the adjustment of all decision individuals in this round, and repeat the steps back to the consensus measurement stage until running to the scheme ranking stage. F'^{k*} L'^{k} F'^{k} d_k Ω_k $\overline{\Omega}$

(4) Scheme ranking

The decision collective fuzzy preference relation that meets the consensus threshold is used as the basis for ranking values, and the order of scheme selection is determined by size, ultimately completing the entire decision. $\overline{F}$

3.4 Case Analysis

This section will further test the effectiveness of the consensus research method of considering decision-makers' emotions in the social network presented in this chapter through actual examples of cooperation between green building engineering project companies and brands of wall insulation materials.

3.4.1 Context of the Problem

Following Case 3.3, further considering that the budget cost that can be compensated for each round of decision-making by the final adjustment opinions of the experts is limited to 3 million yuan, five review experts are now invited again. Based on past experience, it can be estimated that the adjustment cost of the unit preference evaluation opinions corresponding to each of these five review experts can be regarded as (unit:) $D=\{d_1,d_2,\dots,d_5\}$ $\{c_1,c_2,c_3,c_4,c_5\}=\{100,400,300,200,500\}$ The deviation between the adjusted individual opinion and the collective opinion shall not exceed 0.5, that is. $\delta=0.5$ Five review experts are asked to re-evaluate the four brands of wall insulation materials so that the final consensus level meets 0.80 and does not exceed the compensation budget for each round to determine the final cooperation order of the four brands.

$X=\{x_1=\text{Luyang},\ x_2=\text{Jinyu},\ x_3=\text{ABM},\ x_4=\text{Huamei}\}$

To simplify the evaluation process for the four candidate wall thermal insulation material brands, this decision was based on a five-granularity set of language terms for assessment, and the personalized numerical scales corresponding to different language expressions of each review expert were reassigned, and it was assumed that they would not change in the same decision-making process. $S=\{s_0=\text{very bad},\ s_1=\text{bad},\ s_2=\text{ordinary},\ s_3=\text{good},\ s_4=\text{very good}\}$

The initial language preference information for personalized understanding of the language terms by the five reviewers is evaluated as follows.

$L^1=(s_3,s_4,s_0,s_2)$ $L^2=(s_0,s_1,s_2,s_4)$ $L^3=(s_1,s_4,s_3,s_0)$

$L^4=(s_4,s_2,s_0,s_3)$ $L^5=(s_3,s_1,s_2,s_4)$

Table 4. Personalized numerical scales of the language terms corresponding to the reviewers

	NSk(s0)	*NSk(s1)*	*NSk(s2)*	*NSk(s3)*	*NSk(s4)*
d_1	0.15	0.25	0.40	0.75	0.85
d_2	0.20	0.30	0.60	0.70	0.90
d_3	0.10	0.40	0.70	0.90	1.00
d_4	0.25	0.35	0.50	0.75	0.95

d_5	0.35	0.50	0.65	0.80	1.00

According to the emotional classification in Chapter 3, since radical/conservative emotions have less influence, emotional states can be divided into four categories, each mapped by values of

$emo^1 = (suspicious,\ sly)$, $\varphi(emo^1) = 0.2$ $emo^2 = (suspicious,\ stable)$, $\varphi(emo^2) = 0.4$

$emo^3 = (reliable,\ sly)$, $\varphi(emo^3) = 0.6$ $emo^4 = (reliable,\ stable)$, $\varphi(emo^4) = 1.0$

Figure 2. shows the social network relationships among experts, and the obtained distributed trust-sentiment adjacency matrix is DTE

$$\begin{bmatrix}
- & \left(0.7,\left\{\begin{matrix}(emo^1,0.0)\\(emo^2,0.3)\\(emo^3,0.6)\\(emo^4,0.1)\end{matrix}\right\}\right) & \left(0.6,\left\{\begin{matrix}(emo^1,0.2)\\(emo^2,0.1)\\(emo^3,0.3)\\(emo^4,0.4)\end{matrix}\right\}\right) & - & - \\
- & - & \left(0.8,\left\{\begin{matrix}(emo^1,0.7)\\(emo^2,0.0)\\(emo^3,0.2)\\(emo^4,0.1)\end{matrix}\right\}\right) & \left(0.9,\left\{\begin{matrix}(emo^1,0.3)\\(emo^2,0.7)\\(emo^3,0.0)\\(emo^4,0.0)\end{matrix}\right\}\right) & - \\
- & - & - & - & \left(0.7,\left\{\begin{matrix}(emo^1,0.4)\\(emo^2,0.1)\\(emo^3,0.2)\\(emo^4,0.3)\end{matrix}\right\}\right) \\
\left(0.6,\left\{\begin{matrix}(emo^1,0.1)\\(emo^2,0.1)\\(emo^3,0.0)\\(emo^4,0.8)\end{matrix}\right\}\right) & - & - & - & - \\
- & - & - & \left(0.8,\left\{\begin{matrix}(emo^1,0.1)\\(emo^2,0.0)\\(emo^3,0.0)\\(emo^4,0.9)\end{matrix}\right\}\right) & -
\end{bmatrix}$$

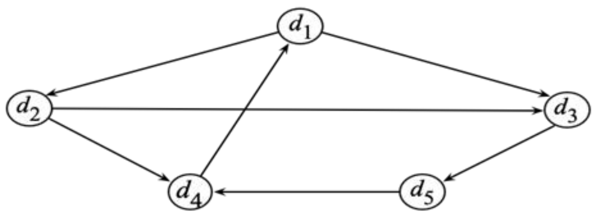


Figure 2. Diagram of the social trust network relationship among review experts

3.4..2 Decision-making process

The language preference evaluation relationship of the five reviewers can be transformed into a fuzzy preference evaluation relationship by referring to the personalized numerical scale of the language terms corresponding to the reviewers in Table 4.1, that is $F^k = (f_1^k, f_2^k, f_3^k, f_4^k),\ k = 1,2,\dots,5$

$F^1 = (0.75, 0.85, 0.15, 0.40)$ $F^2 = (0.20, 0.30, 0.60, 0.90)$ $F^3 = (0.40, 1.00, 0.90, 0.10)$

$F^4 = (0.95, 0.50, 0.25, 0.75)$ $F^5 = (0.85, 0.50, 0.65, 1.00)$

(1) Determine the weights of the experts

According to Equation (20), the distributed trust-sentiment adjacency matrix can be transformed into a direct trust-sentiment adjacency matrix DTE ITE

$$ITE=\begin{bmatrix} - & (0.7,0.58) & (0.6,0.66) & - & - \\ - & - & (0.8,0.36) & (0.9,0.34) & - \\ - & - & - & - & (0.7,0.54) \\ (0.6,0.86) & - & - & - & - \\ - & - & - & (0.8,0.92) & - \end{bmatrix}$$

The indirect trust and sentiment state assessment values seen by the review experts can be calculated with reference to Definition 2.7, and a complete trust-sentiment adjacency matrix can be further formed TE

$$TE=\begin{bmatrix} - & (0.70,0.58) & (0.60,0.66) & (0.28,0.20) & (0.26,0.07) \\ (0.32,0.17) & - & (0.80,0.36) & (0.90,0.34) & (0.35,0.09) \\ (0.27,0.38) & (0.15,0.18) & - & (0.53,0.48) & (0.70,0.54) \\ (0.60,0.86) & (0.38,0.47) & (0.28,0.29) & - & (0.16,0.13) \\ (0.44,0.78) & (0.27,0.42) & (0.15,0.12) & (0.80,0.92) & - \end{bmatrix}$$

According to Equation (21), the trust inclusion center index of the five reviewers can be calculated as

$$C(d_1)=(0.32\times0.17+0.27\times0.38+0.60\times0.86+0.44\times0.78)/4=1.016$$
$$C(d_2)=(0.70\times0.58+0.15\times0.18+0.38\times0.47+0.27\times0.42)/4=0.725$$
$$C(d_3)=(0.60\times0.66+0.80\times0.36+0.28\times0.29+0.15\times0.12)/4=0.761$$
$$C(d_4)=(0.26\times0.07+0.35\times0.09+0.70\times0.54+0.16\times0.13)/4=1.352$$
$$C(d_5)=(0.32\times0.17+0.27\times0.38+0.60\times0.86+0.44\times0.78)/4=0.449$$

Further by Equation (20), the importance weights of the five reviewers can be determined as follows

$$w_1=\frac{C(d_1)}{\sum_{k=1}^{5}C(d_k)}=\frac{1.016}{1.016+0.725+0.761+1.352+0.449}=0.24$$
$$w_2=\frac{C(d_2)}{\sum_{k=1}^{5}C(d_k)}=\frac{0.725}{1.016+0.725+0.761+1.352+0.449}=0.17$$
$$w_3=\frac{C(d_3)}{\sum_{k=1}^{5}C(d_k)}=\frac{0.761}{1.016+0.725+0.761+1.352+0.449}=0.18$$
$$w_4=\frac{C(d_4)}{\sum_{k=1}^{5}C(d_k)}=\frac{1.352}{1.016+0.725+0.761+1.352+0.449}=0.31$$
$$w_5=\frac{C(d_5)}{\sum_{k=1}^{5}C(d_k)}=\frac{0.449}{1.016+0.725+0.761+1.352+0.449}=0.10$$

(2) Consensus measure

Combining Equation (20), the collective fuzzy preference relationship obtained by assembling the individual fuzzy preference relationships of the five review experts is. At this point, the collective consensus level calculated clearly does not meet the set requirement of 0.80 and needs further adjustment. $\overline{F}=(0.66,0.64,0.44,0.60)$ $CL=0.746$

(3) Consensus improvement

It can be calculated from the complete trust-sentiment adjacency matrix TE

$$\sum_{h=2}^{5} Exp(EMO_{h1}) = 0.17 + 0.38 + 0.86 + 0.78 = 2.19$$
$$\sum_{h=1且h\neq 2}^{5} Exp(EMO_{h2}) = 0.58 + 0.18 + 0.47 + 0.42 = 1.65$$
$$\sum_{h=1且h\neq 3}^{5} Exp(EMO_{h3}) = 0.66 + 0.36 + 0.29 + 0.12 = 1.43$$
$$\sum_{h=1且h\neq 4}^{5} Exp(EMO_{h4}) = 0.20 + 0.34 + 0.48 + 0.92 = 1.94$$
$$\sum_{h=1}^{4} Exp(EMO_{h5}) = 0.07 + 0.09 + 0.54 + 0.13 = 0.83$$
$$\min_{\iota=1}^{5} \sum_{h,\iota=1,h\neq\iota}^{5} Exp(EMO_{h\iota}) = 0.83 \quad \max_{\iota=1}^{5} \sum_{h,\iota=1,h\neq\iota}^{5} Exp(EMO_{h\iota}) = 2.19$$

According to definition (21), the probability that five reviewers are willing to adjust is

$$\varpi_1 = \frac{2.19-0.83}{2.19-0.83} = 1 \qquad \varpi_2 = \frac{1.65-0.83}{2.19-0.83} = 0.60 \quad \varpi_3 = \frac{2.19-0.83}{2.19-0.83} = 0.44$$
$$\varpi_4 = \frac{2.19-0.83}{2.19-0.83} = 0.82 \quad \varpi_5 = \frac{0.83-0.83}{2.19-0.83} = 0$$

Integrate the available data and set the adjusted review expert opinion as the adjusted collective preference opinion. $F'^{k} = (f_1'^{k}, f_2'^{k}, f_3'^{k}, f_4'^{k})$ $\overline{F}' = (\overline{f}_1', \overline{f}_2', \overline{f}_3', \overline{f}_4')$

Substituting the adjusted collective preference opinion into Equation (20) of the individual emotion-based maximum effort consensus model (MECM) yields

$$\min \sum_{k=1}^{m} -\mathrm{sgn}\left(\sum_{i=1}^{4}\left(\left|f_i^k - \overline{f}_i\right| - \left|f_i'^k - \overline{f}_i'\right|\right)\right)\cdot \mathrm{sgn}\left(\sum_{i=1}^{4}\left(\varpi_k \cdot f_i'^k - f_i^k\right)\right)\cdot w_k \times \sum_{i=1}^{4}\frac{\varpi_k \cdot f_i'^k - f_i^k}{f_i^k}$$

$$s.t.\begin{cases} f_i'^k - \overline{f}_i' \leq 0.5 \\ f_i'^k - \overline{f}_i' \geq -0.5 \\ \overline{f}_i' = \sum_{k=1}^{5} w_k \cdot f_i'^k \\ CL \geq 0.80 \\ \sum_{k=1}^{5} c_k \cdot \left\{\sum_{i=1}^{4}\left[(f_i'^k - f_i^k)\cdot \mathrm{sgn}(f_i'^k - f_i^k)\right]\right\} \leq 300 \\ f_i'^k, \overline{f}_i' \geq 0 \end{cases}, \qquad i = 1,2,3,4.$$

The individual's best adjusted opinion is solved for

$$F'^{1*} = (0.53, 0.53, 0.91, 0.72) \quad F'^{2*} = (0.20, 0.30, 0.59, 0.88) \quad F'^{3*} = (0.44, 0.82, 0.86, 0.44)$$
$$F'^{4*} = (0.64, 0.50, 0.78, 0.74) \quad F'^{5*} = (0.85, 0.50, 0.65, 0.92)$$

According to Equation (20), the corresponding language evaluation value of the review expert is

$$L'^{1*} = \left[(s_2, 0.36), (s_2, 0.38), s_4, (s_3, -0.08)\right]$$
$$L'^{2*} = \left[(s_0, 0.03), (s_1, 0.01), (s_2, -0.03), (s_4, -0.08)\right]$$
$$L'^{3*} = \left[(s_1, 0.13), (s_3, -0.40), (s_3, -0.20), (s_1, 0.14)\right]$$
$$L'^{4*} = \left[(s_3, -0.46), (s_2, 0.02), (s_3, 0.16), (s_3, -0.03)\right]$$
$$L'^{5*} = \left[(s_3, -0.02), s_1, s_2, (s_4, -0.41)\right]$$

Taking the above formula as the adjusted opinion for reference by the review experts, the actual adjusted opinion of the review experts is

$$L'^{1} = (s_3, s_3, s_1, s_3) \quad L'^{2} = (s_1, s_1, s_2, s_4) \quad L'^{3} = (s_1, s_3, s_3, s_0)$$
$$L'^{4} = (s_4, s_2, s_1, s_3) \quad L'^{5} = (s_3, s_1, s_2, s_4)$$

Refer to Table 4.1 for the transformation, that is

$$F'^{1} = (0.75, 0.75, 0.25, 0.75) \quad F'^{2} = (0.30, 0.30, 0.60, 0.90) \quad F'^{3} = (0.40, 0.90, 0.90, 0.10)$$
$$F'^{4} = (0.95, 0.50, 0.35, 0.75) \quad F'^{5} = (0.80, 0.50, 0.65, 1.00)$$

Then the compensation cost required for each review expert, such as the compensation cost for review experts, is calculated as $\Omega_k = \sum_{k=1}^{5} c_k \cdot \left| f_i'^k - f_i^k \right|$ d_1

$\Omega_1 = 100 \times [|0.75-0.75|+|0.75-0.85|+|0.25-0.15|+|0.75-0.4|] = 55$ ten thousands yuan

By calculating the compensation cost required for the remaining reviewers in the same way, it can be further obtained that the total compensation cost for a single adjustment of ten thousand yuan is less than the budgeted compensation cost for a single adjustment of three million yuan. $\overline{\Omega} = \sum_{k=1}^{5} \Omega_k = 145$

Repeat the consensus measurement process. At this point, the collective consensus level increases to 0.792 but still does not meet the requirements. Therefore, the above steps need to be run again. After this round is completed, the compensation cost of 1.75 million yuan also meets the requirements. As consensus has been achieved, the total compensation cost is 10,000 yuan. The individual and collective fuzzy relationship evaluation opinions of the five review experts are as follows $CL = 0.844$ $145 + 175 = 320$

$F^1 = (0.75, 0.75, 0.40, 0.75)$ $F^2 = (0.30, 0.30, 0.60, 0.90)$ $F^3 = (0.40, 0.90, 0.90, 0.40)$

$F^4 = (0.75, 0.50, 0.50, 0.75)$ $F^5 = (0.8, 0.50, 0.65, 1.00)$ $\overline{F} = (0.62, 0.60, 0.58, 0.74)$

Based on the collective ranking, that is, in combination with the final opinion of all review experts, the cooperation order of the four wall insulation material brands determined by the company for this green building project should be Huamei Rubber & Plastic, Luyang, Jinyu and ABM in sequence. $0.74 > 0.62 > 0.60 > 0.58$ $x_4 \succ x_1 \succ x_2 \succ x_3$

4. Discussion and Analysis of Results

4.1 Result discussion

The efforts of the review experts involved in each round of decision-making and the compensation costs are shown in Table 4., and Figure 2. shows the corresponding changing trends.

It can be observed from the tables and figures that:

Decision-making individuals have different willingness to adjust under different emotional states. Among them, the most positive review experts were willing to adjust with a probability of 1, indicating that they fully accepted the adjustment of the opinion, and corresponding to a higher level of their own effort. Figure 4.3 shows that their effort in the two adjustment processes was always greater than the collective effort, indicating that the review experts tended to promote the realization of the current consensus; d_1 d_1 The most emotionally negative reviewers have a probability of being willing to adjust, which indicates that they completely refuse to revise their preferences. Naturally, their personal effort level is 0, indicating that the reviewers are very stubborn about the original plan view and unwilling to cooperate with the adjustment. Although they do not incur adjustment costs and the compensation cost they receive is 0, it is obviously unfavorable for the consensus to be reached. d_5 d_5

Furthermore, for decision-making individuals in an intermediate emotional state, there is no obvious linear relationship between their efforts to promote consensus and emotional positionality. For example, although the adjustment willingness of the third review expert is lower than that of the first and fourth review experts, and their emotional state is not as good as the latter two, their efforts during the adjustment process are still relatively high, making a significant contribution to achieving consensus. The compensation cost required for decision-making individuals is influenced by consensus effort and unit opinion adjustment cost. The more hardworking the decision-making individuals are, the higher the compensation cost they receive. For example, the compensation cost for the first, third, and fourth review experts is significantly higher than that for the second and fifth review experts who are lower or have no effort.

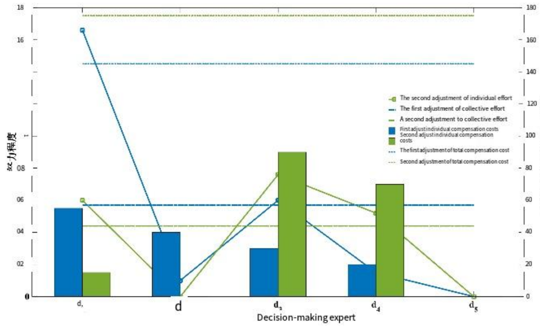


Figure 2. Trends in expert effort and compensation costs

4.2 Comparative analysis

Table 4. shows the differences in consensus level, collective effort, and total compensation cost for individual decision-makers in the decision-making process under the MECM optimization model and the identity-direction rule feedback adjustment path, and Figure 4.4 presents the specific comparison.

The advantages of the optimized consensus model can be clearly seen by referring to the comparisons in Table 4. and Figure 3.

On the one hand, it shortens the consensus process while ensuring a high consensus level, as can be directly seen from Figure 3, the MECM optimized model achieved a collective consensus level of 0.844 in the second round, which is better than the collective consensus level of 0.813 in the third round under the guidance of the identity-direction rule.

On the other hand, with lower cost expenditure and greater contribution of decision-makers to consensus, the total compensation cost generated by the MECM optimization model in each round of decision-making process is lower than the budget consumed in the consensus process guided by the identity-direction rule, and the total compensation cost given by the proposed method in this chapter due to the adjustment opinions of the decision-makers is ten thousand yuan. $(145+175)=320$ A reduction of 1.7 million yuan compared to the total cost of compensation for decision-makers' preference opinion adjustments under the Idential-direction rule, significantly helping to save the total budget cost. $(190+210+90)=490$.

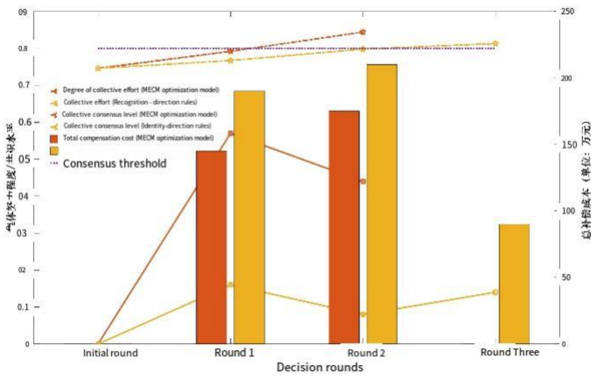


Figure 3. Comparison of consensus processes based on MECM optimization Model and Identity-direction Rule

According to Figure 4.4, in the consensus process guided by the identification direction rules, the collective effort of experts is far less than that in the MECM optimization model, indicating that experts still have considerable room for adjustment under the old feedback mechanism to operate in order to improve the collective consensus level. The model proposed in this chapter takes into full account the experts' emotions and willingness to adjust, and provides accurate and efficient correction suggestions, enabling each expert to make the greatest contribution to consensus achievement, further shortening the decision-making process and improving consensus efficiency. Help to reach a consensus within a limited time.

Table 4. Efforts of 5 Reviewers and Compensation Costs

Compensation cost unit: ten thousand yuan

	$e_1(\varpi_1=1)$	$e_2(\varpi_2=0.6)$	$e_3(\varpi_3=0.44)$	$e_4(\varpi_4=0.82)$	$e_5(\varpi_5=0)$	**Degree of collective effort**
	$\Omega_1(c_1=1)$	$\Omega_2(c_2=4)$	$\Omega_3(c_3=3)$	$\Omega_4(c_4=2)$	$\Omega_5(c_5=5)$	**Total compensation cost** $\overline{\Omega}$
First adjustment	1.66	0.10	0.60	0.15	0.00	0.57
	55	40	30	20	0	145
Second adjustment	0.60	0.00	0.76	0.52	0.00	0.44
	15	0	90	70	0	175

Table 5. Comparison of Consensus Improvement Methods

Compensation cost unit: ten thousand yuan

t	**MECM optimized model**			**Identification - Direction rules**		
	Consensus level	**Degree of collective effort**	**Total compensation cost**	**Consensus level**	**Degree of collective effort**	**Total compensation cost**
Initial	0.746	--	--	0.746	--	--
1	0.792	0.57	145	0.767	0.16	190
2	0.844	0.44	175	0.798	0.08	210
3				0.813	0.14	90

5.Research Conclusions

This study integrates emotions into social networks and explores the impact of emotions on trust relationships among individuals by calculating the trust center index to determine the importance weights of decision-making individuals. In addition, the likelihood of decision-making individuals' willingness to adjust their opinions was determined based on their emotions. In the consensus improvement phase under the feedback mechanism, consider the individual decision-making effort and discuss the issue of the decision-maker's maximum effort consensus. In the language group decision-making of practical problems, the pursuit of satisfaction with collective consensus should also be achieved when budget costs are limited within a certain range. The proposed maximum Effort Consensus Optimization Model (MECM) aims to enable all decision-making individuals to do their best to promote consensus, that is, to maximize their contribution to consensus. The results of solving the model can meet both the consensus level requirements and the cost budget, providing decision-makers with more efficient feedback guidance suggestions. Finally, compared with the identity-direction rule consensus achievement method based on interactive iteration, the proposed method in this paper shows obvious advantages in decision speed, quality and total decision cost, and is more efficient.

AUTHOR CONTRIBUTIONS

Muneef Abdul al Raqeb Taresh Al-Ariqi: Conceptualization; methodology; model development; investigation; writing-original draft; validation; Lishan Xiong: Formal analysis; data curation; case study application; writing-review and editing; supervision.

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CONFLICT OF INTEREST STATEMENT

The authors declare that there are no commercial or financial relationships that could be construed as a potential conflict of interest.

DATA AVAILABILITY STATEMENT

The datasets generated for this study, including numerical examples and simulation outputs, are available from the corresponding author upon reasonable request. All data will be made accessible without undue restriction.

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