Research on Group Decision-Making Model Based on Trust Relationship and Correlation Coefficient in Social Network Environment

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Abstract. Aiming at the consensus adjustment problem of group decision-making in social network context, this paper proposes the consensus adjustment method based on blind thinking behavior's identification. First, the blind thinking behavior coefficient is defined, and the blind thinking behavior identification method is proposed. Then, divide the groups according to the experts' behaviors, take measures for different groups to get the final decision matrix, and calculate the comprehensive gain/loss ratio of the scheme to get the optimal scheme by combining the attribute weights and the TOPSIS method; Finally, the superiority and innovation of the method are verified by the arithmetic examples.

Keywords: Interval intuitionistic fuzzy sets; Social networks; Group decision making; Blind thinking behavior

1 Introduction

In group decision-making, experts' preference value is a very important factor, and in the social network environment, experts' social relations affect their preferences. Therefore, how to integrate social relations into the decision-making process to improve decision quality has become a hot topic nowadays.

Most traditional group decision-making models are based on the assumption of independence of experts and only consider their preferences[1]. Recent studies have shown that integrating social network analysis into group decision-making can effectively improve the science of decision-making and improve the quality of decision-making[2].

In social networks context, Wu[3] developed a trust-based recommendation mechanism, which generates correction suggestions based on the trust relationship and thus obtains a higher level of consensus. Zhang[4] developed a novel consensus framework based on social network analysis to deal with non-cooperative behaviors and thus obtains a mechanism for expert trust propagation and aggregation. Ding[5] proposed a process for investigating conflict relationships based on social network analysis, which distinguishes conflicts into opinion conflicts and behavioral conflicts based on conflict characteristics. Nie[6] defines the unsupported degree function to reflect the degree of disagreement of other experts to the minority opinion, and then adjusts the weights to reach a consensus. Liao[7] identifies two types of conflicts among experts and introduces a conflict resolution model with a feedback

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mechanism for conflict resolution.

Based above, this paper proposes a consensus adjustment method based on blind thinking behavior identification based on social network analysis. The consensus adjustment model is established by defining the blind thinking behavior coefficient. Subsequently, use TOPSIS method to sort the schemes.

2 Principles and Methods

2.1 Interval Intuitionistic Fuzzy Sets

Definition1[8]: Let X be a non-empty set, $A=\{\langle x,\mu_A(x),\upsilon(x)\rangle|\ x\in X\}$ is denoted as an interval number on X, where $\mu_A(x)=[\underline{\mu}_A(x),\overline{\mu}_A(x)]$ and $\upsilon_A(x)=[\underline{\upsilon}_A(x),\overline{\upsilon}_A(x)]$ denotes the subordination and non-subordination degree of the x belonging to the X, where: $\mu_A: X\to(0,1)$, $\upsilon_A(x)$: $X\to(0,1)$, and $0\le\overline{\mu}_A(x)+\overline{\upsilon}(x)\le1$. $\pi_A(x)=[\underline{\pi}_A(x),\overline{\pi}_A(x)]$ denotes the hesitation degree of x belonging to X.

Definition2[9]: Let $A,B\in IVIFS(X)$, the correlation coefficient CC_{AB} of A and B is defined as:

$$K_{IVIFS}(A,B)=\frac{C_{IVIFS}(A,B)}{\sqrt{E_{IVIFS}(A)}\bullet\sqrt{E_{IVIFS}(B)}} \tag{1}$$

Where:

$$C_{IVIFS}(A,B)=\frac{1}{2}\sum_{i=1}^{n}\begin{pmatrix}\underline{\mu}_A(x_i)\underline{\mu}_B(x_i)+\overline{\mu}_A(x_i)\overline{\mu}_B(x_i)\\+\underline{\upsilon}_A(x_i)\underline{\upsilon}_B(x_i)+\overline{\upsilon}_A(x_i)\overline{\upsilon}_B(x_i)\\+\underline{\pi}_A(x_i)\underline{\pi}_B(x_i)+\overline{\pi}_A(x_i)\overline{\pi}_A(x_i)\end{pmatrix},E_{IVIFS}(A)=\frac{1}{2}\sum_{i=1}^{n}\begin{bmatrix}\underline{\mu}_A(x_i)^2+\overline{\mu}_A(x_i)^2+\underline{\upsilon}_A(x_i)^2\\+\overline{\upsilon}_A(x_i)^2+\underline{\pi}_A(x_i)^2+\overline{\pi}_A(x_i)^2\end{bmatrix} \tag{2}$$

2.2 Trust Degree

This paper uses trust matrix to represent trust relationship, based on experts' trust interval values $\overrightarrow{TF}_{pq}=\left(\left[\underline{t}_{pq},\overline{t}_{pq}\right],\left[\underline{r}_{pq},\overline{r}_{pq}\right]\right)$, to obtain a directed trust matrix $\overrightarrow{TM}=(\overrightarrow{TF}_{pq})_{l\times l}$. The directed trust score matrix $\overrightarrow{TSM}=(\overrightarrow{TS}_{pq})_{l\times l}$ is obtained through the trust score function, the trust score matrix $TSM=(TS_{pq})_{l\times l}$ is subsequently obtained through UTWA operator. Trust score function[10] and UTWA operators are defined as follows:

$$\overrightarrow{TS}_{pq}=\frac{\underline{r}_{pq}+\overline{r}_{pq}-\underline{t}_{pq}-\overline{t}_{pq}}{2}+\frac{\underline{t}_{pq}+\overline{t}_{pq}+2\left(\underline{t}_{pq}\overline{t}_{pq}-\underline{r}_{pq}\overline{r}_{pq}\right)}{\underline{t}_{pq}+\overline{t}_{pq}+\underline{r}_{pq}+\overline{r}_{pq}} \tag{3}$$

Definition3: Let $\{\sigma_i=([\underline{t}_i,\overline{t}_i],[\underline{r}_i,\overline{r}_i])|i=1,2,\ldots,k\}$ be the interval trust values set, $\varepsilon=(\varepsilon_1,\varepsilon_2,\ldots,\varepsilon_k)^T$ is the weight vector corresponding to the set. UTWA operator is defined as follows:

$$UTWA_\varepsilon(\sigma_1,\sigma_2,\ldots,\sigma_k)=\begin{cases}\left(\dfrac{\prod_{i=1}^{k}(t_i)^{\varepsilon_i}}{\prod_{i=1}^{k}(t_i)^{\varepsilon_i}+\prod_{i=1}^{k}(1-t_i)^{\varepsilon_i}},\dfrac{\prod_{i=1}^{k}(r_i)^{\varepsilon_i}}{\prod_{i=1}^{k}(r_i)^{\varepsilon_i}+\prod_{i=1}^{k}(1-r_i)^{\varepsilon_i}}\right), & \sigma_i\notin\{(0,1),(1,0)\}\\(0,0), & otherwise\end{cases} \tag{4}$$

3 Decision Modeling

3.1 Problem Description and Modeling

Let $A=\{a_1,a_2\cdots a_{\mathrm{m}}\}$ be alternatives set, $C=\{c_1,c_2\cdots c_{\mathrm{n}}\}$ be attributes set, $\omega=\{\omega_1,\omega_2\cdots\omega_{\mathrm{n}}\}$ be attribute weight, $\mathrm{D}=\{d_1,d_2\cdots d_l\}$ be expert set, $\lambda=\{\lambda_1,\lambda_2\cdots\lambda_l\}$ be expert's weight. d_{p}'s preference matrix is $Y_p=(y_{ij}^p)_{m\times n}=\left(\left[\underline{\mu}_{ij}^p,\overline{\mu}_{ij}^p\right],\left[\underline{\upsilon}_{ij}^p,\overline{\upsilon}_{ij}^p\right],\left[\underline{\pi}_{ij}^p,\overline{\pi}_{ij}^p\right]\right)_{m\times n}$.

According to the preference matrix, based on Eq.(1) and attribute weights ω, calculate the correlation coefficient matrix $CCM=(CC_{pq})_{l\cdot l}$. Based on the directed trust matrix $\overrightarrow{TM}$, using Eq.(4)(5) to calculate the trust score matrix $TSM=(TS_{pq})_{l\times l}$ .Based on expert weights, use IVIFWA operator to assemble the preference matrices to obtain a temporary comprehensive preference matrix $\tilde{R}=\left(\tilde{r}_{ij}\right)_{m\times n}=\left(\sum_{p=1}^{l}\lambda_p y_{ij}^p\right)_{m\times n}$.

3.2 A Consensus Adjustment Model Based on Blind Thinking Recognition

In group decision-making process, experts may have blind thinking that affects the results[11, 12]. In addition, most decision models are based on majority principle. However, the majority may not be fully justified, especially for emergency issues, such issues need to be fully discussed to rationalize the results, and the presence of a minority opinion in the decision-making process means that the result is more comprehensive. Therefore, this paper follows up the study by classifying types of conflicts.

3.2.1 Preference Conflict Identification

This paper calculates individual preference and trust conflict based on TSM and CCM, then derives the degree of group preference conflict. By combining the hesitation degree to define the blind thinking coefficient, based on this, decision-making groups are divided and measures are taken separately to achieve rational decision-making results.

For d_p, its preference conflict $\sigma_p^C=1-K_{IVIFS}\left(Y_p,\tilde{R}\right)=1-\frac{1}{m}\sum_{i=1}^{m}\sum_{j=1}^{n}\omega_j\cdot K_{IVIFS}\left(y_{ij}^p,r_{ij}\right)$, trust conflict $\sigma_p^T=1-\frac{1}{l-1}\sum_{q=1,q\neq p,}^{l}TS_{pq}$. Let σ^C and σ^T be preference conflict and trust conflict thresholds, when σ_p^C and σ_p^T are greater than threshold, consider d_p has preference conflict or trust conflict. The degree of group preference conflict $\phi=\frac{1}{l}\sum_{p=1}^{l}\sigma_p^C$.

Definition4: Based on trust and preference conflict degree, define the blind thought coefficient as:

$$\gamma\left(d_{\mathrm{p}}\right)=\left(\frac{1}{1+e^{-6\left|\sigma_p^C\cdot\sigma_p^T-0.2\right|}}\right)\left(\frac{\sigma_p^C\cdot\sigma_p^T}{\left(\sigma_p^C\right)^2+\left(\sigma_p^T\right)^2-\sigma_p^C\cdot\sigma_p^T}\right)e^{\bar{\pi}_p}\tag{5}$$

After obtaining the blind thinking coefficient and normalizing it, by setting the blind thinking coefficient threshold γ and combining σ^C and σ^T, the decision-making group is classified as: (1) Experts' $\gamma_p \geq \gamma$ and have preference and trust conflict were considered to have conflict blind thinking.(2) Experts' $\gamma_p < \gamma$ and have preference conflict were considered to have no blind thinking but a different opinion.(3) Experts' $\gamma_p < \gamma$ and have relational conflicts were considered to have no blind thinking, their preferences should be highlighted for reference.(4) Experts' $\gamma_p \geq \gamma$ and without preference and trust conflicts were considered to have trust blind thinking. (5) Experts' $\gamma_p < \gamma$ and without preference and trust conflicts, they represent the majority opinion, their preferences should be highlighted for reference.

If $\phi \notin [\underline{\phi}, \overline{\phi}]$, arrange class (2)(3)(5) experts to explain their preferences so that both majority and minority opinions were effectively discussed. In addition, the combined decision results of the class (3)(5) were used as a benchmark for subsequent preference adjustment.

3.2.2 Preference Adjustment Methods

(1) Comprehensive Correct Coefficient

This paper adjusts expert preferences by analyzing their conflict behaviors, focusing on hesitancy to calculate objective correction coefficients, and combining them with subjective correction coefficients to obtain comprehensive correct coefficients.

First, d_p in class (1)(2)(4) are asked to give subjective correction factors $\eta_p^S (0 \leq \eta_p^S \leq 1)$.

Definition5: For d_p in class (1)(4), the objective correction coefficient η_p^O is defined as:

$$\eta_p^O = \frac{1}{1 + e^{-6\left|\sigma_p^C \cdot \sigma_p^T - 0.2\right|}} \hat{\pi}_p \tag{6}$$

The comprehensive correction factor η_p for d_p in class (1)(4) is determined by the following principles. Principle I: if $\eta_p^S \geq \eta_p^O$,then $\eta_p = \eta_p^S$; Principle II: if $\eta_p^S \leq \eta_p^O$,then $\eta_p = (\eta_p^S + \eta_p^O)/2$;

(2) Preference modification

For d_p in class (1), to eliminate the effect of trust conflict on their preferences, the adjustment formula is:

$$Y_p = \left(1 - \eta_p\right) Y_p + \eta_p \cdot R_3 \tag{7}$$

For d_p in class (2), modifying their preferences by their subjective modification factor, the adjustment formula is:

$$Y_p = \left(1 - \eta_p^S\right) Y_p + \eta_p^S \cdot R_3 \tag{8}$$

For d_p in class (4), to eliminate the effect of over-trust on their preferences, the adjustment equation is:

$$Y_q = \left(1 + \eta_q\right) Y_q - \eta_q \cdot R_3 \tag{9}$$

The consensus adjustment algorithm is obtained as follows.

First, managers need to determine the maximum adjustment times $C_{\max}$, the group preference conflict interval $[\underline{\phi},\overline{\phi}]$, the preference and trust conflict threshold σ^C σ^T, and the blind thinking coefficient threshold γ.

Step 1: Collect the expert preference matrix and directed trust matrix, get the correlation coefficient matrix by Eq. (1), get the undirected trust score matrix by Eq. (3)(4), set $C = 0$.

Step 2: Obtain integrated decision matrix $\tilde{R}$, then calculates experts' conflict degree and the degree of conflict of group preferences. If $\phi \in [\underline{\phi},\overline{\phi}]$, go to step 6, otherwise go to step 3;

Step 3: Calculate γ_p and divide the group according to σ^C, σ^T and γ.

Step 4: Ask class (2) to explain their preferences and discuss, calculate the combined preferences R of class (3)(5) as the subsequent adjustment benchmark, ask class (1)(2)(4) to give η_p^S, and for the experts of class (1) (4), combine η_p^S and η_p^O to get η_p;

Step 5: If $\phi > \overline{\phi}$, then adjust class (1)(2) preferences by Eq.(7)(8); If $\phi < \underline{\phi}$, adjust class (4) preferences by Eq.(9). Set $C = C+1$, if $C = C_{\max}$, go to step 6, else, return to step 2;

Step 6: End iteration and get the final adjust times $C^* = C$, combine attribute weights to generate the final matrix $\tilde{R}$;

Step 7: Based on TOPSIS and attribute weights to get each scheme's closeness with the positive and negative ideal schemes, which in turn leads to the combined gain/loss ratio. Finally, obtain the optimal solution that maximizes the combined profit/loss ratio.

4 Numerical example and analysis

Early 2022, the Omicron virus spread rapidly, a city organized eight experts to discuss the epidemic prevention measures, three options were identified: a_1: Keeping normal traffic, sealing off and controlling the areas where infected cases are located, and imposing a mandatory quarantine on those who enter the city from infected areas. a_2: Seal all roads in the city, focus on testing areas where outbreaks are occurring, and enforce quarantine of all outsiders. a_3: Keeping traffic normal, conducting epidemiological investigations, quarantining medium- and high-risk areas, and mandatory quarantine for those entering the city.

For three options, the command identified three attributes, "economic benefit", "time benefit", and "level of morbidity and mortality control", and determined their weights as $\omega = \{0.3, 0.35, 0.35\}$, decision-making groups weighted as $\lambda = \{0.16, 0.11, \ldots, 0.09\}$.

Before modeling, manager determine the maximum number of conflict adjustments $C_{\max} = 6$, the group preference conflict interval $[\underline{\phi},\overline{\phi}] = [0.10, 0.18]$, the preference and trust conflict threshold $\sigma^C = 0.3$, $\sigma^T = 0.3$, and the blind thinking coefficient threshold $\gamma = 0.8$.

Step 1: Collect preference matrix as shown in Table1 and directed trust matrix to obtain CCM and TSM, set $C = 0$.

Step 2: Get $\tilde{R}$ as shown in Table2, then obtain conflict degree of each expert as shown in Table3, the group preference conflict degree ϕ =0.31, so go to step3.

Step 3：Get $\gamma\left(d_{\mathrm{p}}\right)$ and classify the group based on $\sigma^{C}, \sigma^{T}, \gamma$ as shown in Table4.

Step 4：Let class (2) experts explain preferences. Calculate the combined decision result of class (3)(5) experts as the consensus adjustment benchmark for this round. Then, combine η_p^S of class (1)(2)(4) and η_p^O of class (1)(4) to get η_p of the experts as shown in Table5.

Step 5: This round $\phi > \bar{\phi}$， use Eq.(7)(8) to adjust class(1)(2) preference，and set $C = C + 1$. Return step2 to recalculate $\tilde{R}$， and iterate until ϕ reaches the required interval.

Step 6: After 4 iterations, ϕ reaches the requirement and $\tilde{R}$ is generated by combining ω as shown in Table6.

Step 7: Based on $\tilde{R}$, calculate scheme's closeness with the positive and negative ideal schemes, then get the scheme that ends up with the largest combined profit/loss ratio is a_3.

Table 1. Preference Matrix

	c_1	c_2	c_3
d_1			
a_1	([0.48,0.52],[0.4,0.42],[0.06,0.12]	([0.36,0.42],[0.45,0.52],[0.06,0.19])	([0.77,0.82],[0.13,0.15],[0.03,0.1])
a_2	([0.25,0.33],[0.65,0.67],[0,0.1]	([0.52,0.55],[0.31,0.35],[0.1,0.17])	([0.61,0.65],[0.25,0.28],[0.07,0.14])
a_3	([0.2,0.25],[0.7,0.72],[0.03,0.1]	([0.71,0.75],[0.11,0.15],[0.1,0.18])	([0.58,0.60],[0.33,0.35],[0.05,0.09])
d_2			
a_1	([0.45,0.51],[0.25,0.3],[0.19,0.3]	([0.32,0.36],[0.31,0.35],[0.29,0.37])	([0.7,0.75],[0.10,0.12],[0.13,0.2])
a_2	([0.2,0.28],[0.51,0.55],[0.17,0.29]	([0.45,0.48],[0.25,0.31],[0.21,0.3])	([0.58,0.6],[0.15,0.2],[0.2,0.27])
a_3	([0.16,0.20],[0.56,0.61],[0.19,0.28]	([0.68,0.71],[0.05,0.11],[0.18,0.27])	([0.61,0.65],[0.22,0.25],[0.1,0.17])
⋮			
d_8			
a_1	([0.56,0.61],[0.26,0.31],[0.08,0.18]	([0.45,0.51],[0.37,0.42],[0.07,0.18])	([0.63,0.68],[0.24,0.27],[0.05,0.13])
a_2	([0.45,0.51],[0.39,0.44],[0.05,0.16]	([0.57,0.61],[0.28,0.33],[0.06,0.15])	([0.73,0.77],[0.13,0.17],[0.06,0.14])

a_3	([0.51,0.56],[0.33,0.38],[0.06,0.16]	([0.69,0.73],[0.18,0.22],[0.05,0.13])	([0.59,0.63],[0.26,0.29],[0.08,0.15])

Table 2. Provisional Integrated Decision Matrix

$\tilde{R}$	c_1	c_2	c_3
a_1	([0.48,0.52],[0.4,0.42],[0.06,0.12])	([0.36,0.42],[0.45,0.52],[0.06,0.19])	([0.61,0.65],[0.25,0.28],[0.07,0.14])
a_2	([0.25,0.33],[0.65,0.67],[0,0.1])	([0.52,0.55],[0.31,0.35],[0.1,0.17])	([0.77,0.82],[0.13,0.15],[0.03,0.1])
a_3	([0.45,0.49],[0.43,0.48],[0.03,0.12]	([0.71,0.75],[0.11,0.15],[0.1,0.18])	([0.58,0.60],[0.33,0.35],[0.05,0.09])

Table 3.Expert Conflict Levels for Round 1

Expert	Preference Conflict	Trust Conflict
d_1	0.21	0.13
d_2	0.23	0.09
$\vdots$	$\vdots$	$\vdots$
d_8	0.38	0.15

Table 4. Classification of experts for round 1

Type of Expert	Number	Expert
Type1	1	$\{d_7\}$
Type2	1	$\{d_8\}$
Type3	3	$\{d_3,d_4,d_6\}$
Type4	1	$\{d_2\}$
Type5	2	$\{d_1,d_5\}$

Table 5. Expert preference correction factors

Expert	Subjective coefficient	Objective coefficient	Integration coefficient
d_2	0.14	0.34	0.24
d_7	0.25	0.33	0.29
d_8	0.22	-	0.22

Table 6. Integrated Decision Matrix

$\tilde{R}$	c_1	c_2	c_3
a_1	([0.44,0.48],[0.43,0.45],[0.07,0.13])	([0.39,0.42],[0.45,0.52],[0.06,0.16])	([0.66,0.68],[0.22,0.25],[0.07,0.12])
a_2	([0.28,0.33],[0.65,0.67],[0,0.1])	([0.50,0.53],[0.33,0.37],[0.1,0.17])	([0.78,0.81],[0.12,0.15],[0.04,0.1])

a_3	([0.48,0.51],[0.43,0.46],[0.03,0.09]	([0.69,0.73],[0.21,0.25],[0.02,0.1])	([0.63,0.66],[0.29,0.33],[0.01,0.08])

5 Conclusion

This paper studies the group decision-making problem in the social network environment. Aiming at the possible blind thinking behavior in decision-making groups, a group decision-making model based on trust relationship and correlation coefficient is established based on social network analysis. A blind thinking behavior identification and processing method is proposed to divide the decision-making group and adjust the preference for different groups respectively. The effectiveness and innovativeness of this paper's method are illustrated through case studies.

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