Hindawi
Journal of Mathematics
Volume 2022, Article ID 2842601, 14 pages
https://doi.org/10.1155/2022/2842601

Research Article

Large-Scale Group Decision-Making Model with Cooperative Behavior Based on Social Network Analysis considering Propagation of Decision-Makers' Preference

Shizhen Bai,[1] Hao He ,[1] Mengke Ge ,[2] Ruobing Yang ,[1] Dan Luo ,[1] and Xinrui Bi [1]

[1]*School of Management, Harbin University of Commerce, Harbin 150028, China*
[2]*School of Mathematical Sciences, Mudanjiang Normal University, Mudanjiang 157012, China*

Correspondence should be addressed to Hao He; he156958505@163.com

Received 17 April 2022; Revised 21 May 2022; Accepted 24 May 2022; Published 9 July 2022

Academic Editor: Gohar Ali

This paper proposes a large-scale group decision-making model with cooperative behavior based on social network analysis considering propagation of decision-makers' preference, which is applicable for large-scale group decision-making problems in social network contexts. The main contributions of our research are three aspects. Firstly, a novel calculation method of cooperative degree, hesitant degree, and noncooperative degree is developed, which considers both the network status and the preference for each DM, and thereby it can better represent the current state for each DM. Then, the determination method of each DM's weight is presented, which considers both the individual network centrality and preference similarity degree. In addition, the score for the current cooperation situation is performed, and the improvement algorithm of the increase of cooperative degree and the decrease of noncooperative degree is designed to enhance the quality of the decision-making results. Finally, the proposed model has demonstrated the validity and superiority based on the comparative and sensitive analysis through a practical example.

1. Introduction

With the increasing complexity of decision-making problems and the increasing number of decision-makers (DMs), the large-scale group decision-making (LSGDM) problem has attracted many scholars' attention [1–8]. LSGDM is the process of selecting the best option from the opinion of many DMs (at least 20 [9]), who express their preferences based on the decision-making information provided for alternatives. In LSGDM problems, DMs usually come from different interest groups, and their status, expertise, and understanding of the problem are different. So, they tend to have different preferences and assessments for the available decision alternatives. Different preferences between DMs may cause conflicts within the decision-making group, which is unfavorable for the whole LSGDM process, and it is also not conducive to the objectivity of the final decision-making results. Moreover, the disharmony within the decision-making group may also cause noncooperative behavior between DMs, which is extremely unfavorable to the flow of information within the decision-making group. Therefore, it is beneficial to increase the overall cooperation degree of the group and decrease the noncooperation degree of the group for LSGDM problems.

The relationship between members of society has become more and more important and complex. In LSGDM problems, the relationship between DMs can be divided into three types: positive, neutral, and negative [6]. Apparently, the closer and more friendly the relationship between DMs is, the more conducive it is to the propagation of preference in the whole decision-making process. If the majority of DMs actively participate in LSGDM problems and their relationships are positive and friendly, it is easier to listen to others and reach a consensus. Conversely, if there are many DMs who hold negative attitudes toward LSGDM problems and their relationships are almost negative, it will be quite difficult to reach an ideal degree of consensus. Specifically, after a DM expresses his/her preference information through the relationship, other DMs will rethink their own preference information in detail, thereby revising their preference information. Therefore, increasing the cooperative behavior and reducing the noncooperative behavior within the decision-making group are not only conducive to the propagation of preference information but also favorable to the objectivity of the final decision-making results.

To increase the cooperation between DMs and raise it to an acceptable level of the decision-making events, a frequently used method is to decrease the weight of those who have noncooperation [4, 10, 11], which aims to reduce its impact on the overall decision-making process. It is widely believed that the noncooperative behavior between DMs derives from their different individual preferences for alternatives, which affects the consensus reaching processes (CRP) [7, 8]. The analysis of noncooperative behavior in the CRP mainly focuses on the influence on reaching group consensus and finding the best alternative [12]. However, existing studies mainly focus on the reduction of noncooperative behavior, rarely on the hesitation of DMs and the improvement of cooperative behavior. In this study, the behavior of DMs is divided into cooperative, hesitant, and noncooperative behavior. Therefore, our research aims to address the following questions:

(a) In such contexts, how to define cooperation degree, hesitant degree, and noncooperation degree for each DM?

(b) How to give the weight of each DM, taking into account the network status and preference of DMs?

(c) What is the effect on decision-making results considering the propagation of the DMs' preference? And what is the advantage of the proposed model?

In this study, intuitionistic fuzzy sets (IFSs) theory is used to express the cooperation degree and noncooperation degree of DMs because the membership degree and nonmembership degree can greatly represent them. Meanwhile, social network analysis (SNA) which is an effective tool to study the relationship among members of society [13] is used to express and quantify the relationship strength between DMs. And the propagation of the preference information of DMs is related to the relationship strength. If the relationship between two individuals is strong, it is easier for them to share information, thereby affecting the other's opinions. Conversely, if the relationship between them is weak, the degree of information propagation may be lower [14, 15]. In addition, the weight of the DMs is also important in LSGDM problems, which has a great impact on the result of the final decision-making. In this study, we propose a determination method of each DM's weight, which considers both the individual network centrality and preference similarity degree, resulting in a more accurate decision-making result.

In summary, although the relationship between DMs is critical in the decision-making process, the existing research mainly focuses on the degree of cooperation and noncooperation and rarely considers the hesitation of DMs in the process of preference propagation. Our research fills this gap that a novel LSGDM model with the cooperative behavior considering the propagation of preference based on SNA is proposed. An important innovation in the proposed model is considering both the cooperative behavior and DMs' attitude. The main contributions are as follows:

(1) A novel calculation method of cooperative degree, hesitant degree, and noncooperative degree is developed, which considers both the network status and the preference for each DM; thereby, it can better represent the current state for each DM.

(2) A determination method of each DM's weight is presented, which considers both the individual network centrality and preference similarity degree.

(3) The score for the current cooperation situation is performed, and the improvement algorithm of the increase of cooperative degree and the decrease of noncooperative degree is designed to enhance the quality of the decision-making results.

The rest of this paper is organized as follows. A systematic literature review is conducted in Section 2. Section 3 presents two paramount concepts of intuitionistic fuzzy sets and social network analysis. In Section 4, the calculation method of cooperative degree, hesitant degree, and noncooperative degree for each DM is developed. The judgment process of decision-making and the adjustment process of DMs' cooperative degree and noncooperative degree are performed in Section 5. In Section 6, the proposed model is applied to an example that selects the location problem of a garden company to illustrate and validate its feasibility and superiority. In the last section, we summarize the innovations and express the limitations of this study.

2. Literature Review

Due to the development of information technology and self-media, the relationship between members of society has become more and more complicated. Researchers have paid more attention to the relationship between DMs in LSGDM problems. Social network, which involves the relationship between people, refers to an interactive network formed by the interaction between members of society [16]. Social network analysis (SNA) is an effective tool for studying the relationship among members of society [13]. Liu et al. [17] used the SNA to develop a conflict detection and elimination decision-making process. Chu et al. [1] applied the closeness of social group centrality of community to measure its importance and proposed a procedure for LSGDM with fuzzy preference relations based on social network community analysis. Xu et al. [16] obtained attributes by mining public big data on social platforms, then constructed a social network based on trust relationship and opinion similarity among DMs, and used a clustering method that considered both trust and similarity to cluster DMs and thereby to obtain their weights based on SNA.

In addition, due to the relationship among DMs being considered in LSGDM, the consensus level of the whole decision-making problem is inevitably low. Therefore, studying the cooperative and noncooperative behavior among DMs is of significance for LSGDM. Zhang et al. [18] proposed a personalized individual semantics- (PIS-) based individual consensus-level maximization model and established a PIS-based minimum adjustment model for consensus reaching in linguistic GDM. Gao et al. [19] developed a consensus reaching algorithm with noncooperative behavior management for social network GDM problem based on PIS and designed a novel management mechanism to dynamically adjust social network trust. However, DMs may use the unbalanced linguistic information to express their opinion on GDM. Zhang et al. [20] proposed a consensus algorithm considering the limited confidence level and the minimum adjustment to the DMs' linguistic evaluation.

Furthermore, many scholars have proposed many LSGDM approaches from the perspective of practice and application. Chen et al. [21] determined passenger demands and evaluated their satisfaction by using a combination of online review analysis and LSGDM based on a case study of high-speed rail system in China. Xiao et al. [22] established the civil engineering construction contractor selection framework in the LSGDM environment through considering the interaction within and between the management layers of the consensus model.

Therefore, in the social contexts, developing an LSGDM with cooperative behavior considering the propagation of DMs' preference is of significance to further understand the complex relationship among DMs and thereby obtain a more scientific and accurate decision result.

3. Preliminaries

In this section, the concepts of intuitionistic fuzzy sets (IFSs) and social network analysis (SNA) are introduced, respectively.

3.1. Intuitionistic Fuzzy Sets. In this paper, intuitionistic fuzzy sets (IFSs) are conducted because it is appropriate for use to express the DMs' hesitancy. The concept of IFS was introduced by Atanassov [23] as follows.

Definition 1. Let X be a nonempty real number set. The IFS A in X is an object in the form

$$A = \{x, t_A(x), f_A(x) | x \varepsilon X\}, \tag{1}$$

where $t_A(x) \in [0,1]$ represents the membership degree and $f_A(x) \in [0,1]$ represents the nonmembership degree. For an IFS A, $\pi_A(x)$ is called the hesitation degree of x to A if $\pi_A(x) = 1 - t_A(x) - f_A(x)$. Obviously, the value of $\pi_A(x)$ satisfies $0 \leq \pi_A(x) \leq 1$. Particularly, A is reduced to a fuzzy set if $\pi_A(x) = 0$ for all $x \in X$.

3.2. Social Network Analysis. The notion of a social network and the methods of SN analysis have attracted many studies which are helpful in analyzing the relationships between social entities [24] and the patterns and influences of these relationships [25]. Social network analysis studies the relationship between social entities, such as members of a group, corporations, or nations [26].

There are two main concepts in a network that are nodes and edges. Nodes, also called actors in social networks, can be regarded as the DMs in LSGDM problems. Edge among the actors, also called relationships in social networks, can be denoted as links between DMs in LSGDM problems. There are three classical representation methods [26, 27] for the nodes' relationship in a social network, as shown in Table 1.

The social network has four actors and six directed edges in Table 1. The direct edges, the relationships among the actors, are represented as a number 1 in the adjacency matrix. For the actors who do not have direct edges in the graph, it is expressed as 0 in the adjacency matrix.

In a social network, there are three relationships between these nodes: direct, indirect, and irrelevant relationships. If there is a direct relationship from e_i to e_j, there is an edge from e_i to e_j in a social network, as shown in Figure 1(a). If there is an indirect relationship from e_i to e_j, it is not a direct relationship, but e_i can establish a potential path to e_j through several mediators in the social network, as shown in Figure 1(b). Besides these, if e_i and e_j are neither direct nor indirect relationship, then it implies that there is an irrelevant relationship between e_i and e_j, as shown in Figure 1(c).

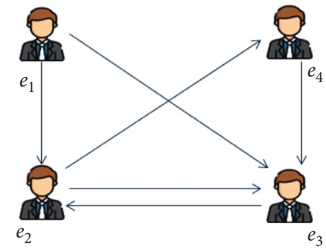
4. LSGDM Process with Social Network

4.1. Basic Concepts of Individual Preference Propagation among DMs in LSGDM Problems. Let $X = \{x_1, \ldots, x_p, \ldots, x_P\} (P \geq 2)$ be the set of alternatives, $E = \{e_1, \ldots, e_m, \ldots, e_M\} (M \geq 20)$ be the set of experts and DMs, and $F = \{f_1, \ldots, f_n, \ldots, f_N\} (N \geq 2)$ be the set of attributes for each alternative. DM e_m provides his or her evaluation information matrix at the t-th stage $Q^{m,t} = (q_{p,n}^{m,t})_{P \times N}$ $(m = 1, \ldots, M)$, where $q_{p,n}^{m,t}$ represents the evaluation value of the attribute f_n on the alternative x_p for the DM e_m at the t-th stage. The weight for each attribute is predefined as w_n $(n = 1, \ldots, N)$.

In social network, the individual preference of a DM will be affected by the spread of other DMs' individual preference. In this process, the relationship between DMs will change. In this paper, we consider that the individual preference of a DM propagates via relationship and similarity. Therefore, we believe that it is still an important factor in DMs' preference propagation process. And preference similarity is an important factor in the evolution process of DMs' individual preference. In this paper, we consider that (a) the preference of a DM will be stable after several stages and (b) the relationship strength and preference similarity are variable through DMs' preference propagation process.

Direct relationship information in a social network can be gathered, such as through questionnaires or interviews. Relationship strength is a quantitative expression of the contact frequency or friendliness degree among DMs [28]. In this study, $rs_{i,j}^t$ is denoted as the value of relationship strength from e_i to e_j at the t-th stage and satisfies condition $0 \leq rs_{i,j}^t \leq 1$. The higher its value, the closer the relationship

Table 1: Three representation methods in social network analysis.

Sociomatrix	Algebraic	Graph theoretical
$A = \begin{array}{c c} & \begin{array}{cccc} e_1 & e_2 & e_3 & e_4 \end{array} \\ \begin{array}{c} e_1 \\ e_2 \\ e_3 \\ e_4 \end{array} & \left(\begin{array}{cccc} 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{array}\right) \end{array}$	$e_1 \mathrm{R} e_2$ $e_1 \mathrm{R} e_3$ $e_2 \mathrm{R} e_3$ $e_2 \mathrm{R} e_4$ $e_3 \mathrm{R} e_2$ $e_4 \mathrm{R} e_3$	

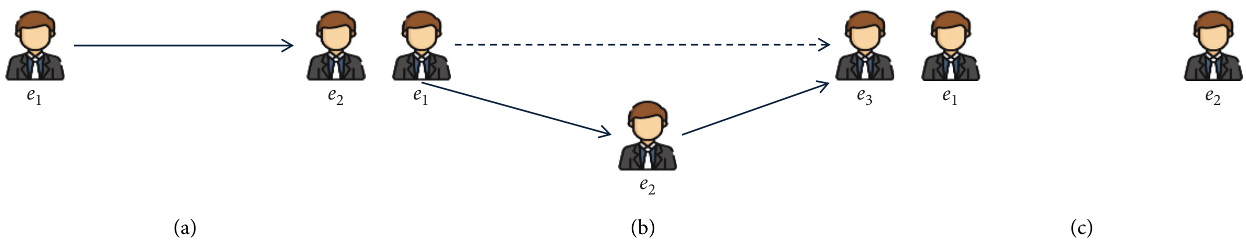


Figure 1: An example of social network to illustrate types of relationship. (a) Direct relationship. (b) Indirect relationship. (c) Irrelevant relationship.

between two DMs and the more meaningful and detailed the preferences. Particularly, the value of $rs^t_{i,j}$ is 1 if i is equal to j, and the value of $rs^t_{i,j}$ is 0 if e_i has no direct relationship to e_j. $RS^t = (rs^t_{i,j})_{P\times P}$ represents the relationship strength matrix at the t-th stage. Taking Figure 2 as an example, we can obtain RS^t to represent the social network as follows:

$$RS^5 = \begin{pmatrix} 1 & 0.5 & 0.7 \\ 0 & 1 & 0 \\ 0.9 & 0 & 1 \end{pmatrix}. \quad (2)$$

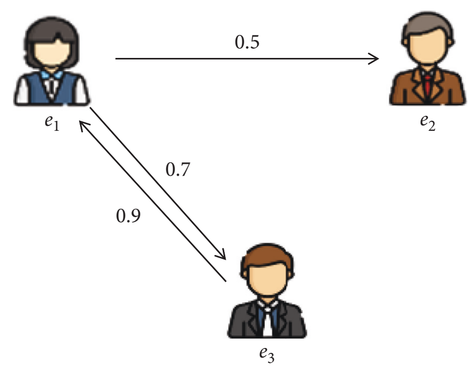


Figure 2: A social network at the 5-th stage.

4.2. The Illustration of Cooperative Degree and Noncooperative Degree. Related studies focus on the relationship and behavior between DMs, such as the noncooperative behavior management [4, 5, 11, 29–31] and trust relationship management [4, 17, 24, 32]. However, the relationship among DMs is more complex and uncertain. Specifically, the DMs may be hesitant about the linguistic variables or assessment information needed to express their preferences. Torra [33] first proposed hesitation fuzzy sets (HFSs) to deal with hesitation situations. Similarly, in addition to cooperative and noncooperative behavior, hesitation should also be considered. Therefore, in this study, cooperative degree, noncooperative degree, and hesitation degree are used to measure how DMs' social relationships affect their assessment information.

Cooperation refers to the behavior of group members working together to achieve common goals. For a DM, his or her cooperation is the willingness to cooperate with other DMs. In social relationship, the cooperative willingness of DMs is the intimacy degree with other DMs, that is, the out-degree of a DM in a social network. The larger the value of the out-degree of a node, the higher the DM's cooperative willingness for others. Therefore, in this paper, the cooperative degree of a DM is considered as a function of the intimacy degree of a DM, that is, the relationship out-degree of a node in a social network.

Definition 2. Suppose that the cooperative degree of e_i is denoted as cd_i, the relationship out-degree of e_i in the social network is od_i, and then the cooperative degree is defined as

$$cd_i = 1 - \cos\left(\frac{\pi \cdot od_i}{2}\right). \quad (3)$$

Clearly, the value of cd_i is in the interval of [0,1]. A plot represents the values taken by cd_i (od_i) on the domain of [0,1], as shown in Figure 3.

Similarly, the relationship out-degree od_i in the social network is defined as

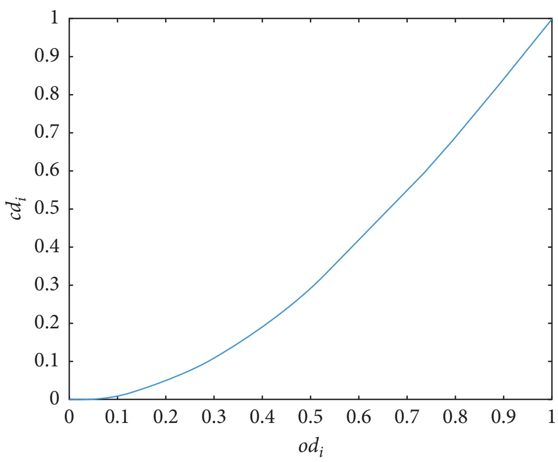


FIGURE 3: The plot of the cooperative degree function.

$$od_i = \frac{\sum_{t=1}^{T}\sum_{j=1,j\neq i}^{P}\sin\left(rs_{i,j}^{t}\right)}{T\cdot S_i}, \tag{4}$$

where S_i is a set that DM e_i thinks he has a direct relationship with others and $\#S_i$ represents the number of S_i and satisfies condition $0\leq{}^{\#}S_i\leq P$.

Hesitant degree represents the degree of hesitation of DMs when deciding their own behavior (cooperation or noncooperation), which can reflect the uncertainty of DMs' choice of their own behavior to a certain extent. Generally speaking, the hesitant degree of a DM is related to the familiarity and preference similarity of other DMs. When there is a relationship between e_i and e_j, if e_i thinks that the relationship between him and e_j is so close and e_j thinks that the relationship between him and e_i is also familiar, the value of relationship strength is so high, and the stronger the cooperative behavior between them, the lower their hesitant degree. Conversely, if DM e_i thinks that the relationship between him and another DM e_j is so close but e_j believes that the relationship between himself and e_i is not familiar, that is, the value of relationship strength is small, the hesitant degree should be high. Therefore, in a social network, if the difference between in-degree and out-degree of a node is higher, the hesitant degree is then larger, and vice versa.

Furthermore, when there is no relationship between e_i and e_j, the higher the preference similarity between e_i and e_j, the greater the possibility of cooperative behavior between them and the lower the hesitant degree. Therefore, in this study, the hesitant degree of a DM is considered as a function of the difference between in-degree and out-degree of a node in a social network and the preference similarity between himself and others. The equation of the hesitant degree is as follows:

$$hdi = \frac{1}{2}\frac{\sum_{t=1}^{T}\sum_{j=1,j\neq i}^{P}\sin\left|(\pi/2)\left(rs_{i,j}^{t}-rs_{j,i}^{t}\right)\right|}{T\cdot\#S_i}+\frac{1}{2}\frac{\sum_{t=1}^{T}\sum_{e_j\in EQ_i}\mathrm{simi}\left(e_i,e_j\right)}{T\cdot\left(M-\#S_i\right)}, \tag{5}$$

where *simi* (e_i, e_j) represents a function that the preference similarity between e_i and e_j and the equations are as follows:

$$\mathrm{simi}\,(ei,ej) = 1-\frac{\sum_{p=1}^{P}\sum_{n=1}^{N}\left|Q^{i,t}-Q^{j,t}\right|}{P\cdot N}. \tag{6}$$

Obviously, the larger the number of *simi* (e_i, e_j), the greater the preference similarity between e_i and e_j. As mentioned above, the noncooperative degree is

$$ndi = 1-cdi-hdi. \tag{7}$$

4.3. The Determination of the DMs' Weights. In this study, we think that the DMs' weights are related to the difference between the DM's preference and the collective preference and the individual network centrality. Specifically, if the difference between a DM's preference and the collective preference is lower, the similarity between the DM's preference and the collective is greater, and the DM should obtain a larger weight. Conversely, the larger the difference between the DM's preference and the collective, the less the preference similarity between the DM and the collective, and the DM's weight should be decreased to a certain extent. Also, if the individual network centrality of a DM is larger, the importance of the DM in a social network is greater, his opinions are of higher importance, and a higher weight should be thus assigned to him. On the contrary, the less the individual network centrality of a DM, the lower the importance of the DM in a social network, and the DM's weight should be then reduced appropriately. Therefore, the calculation equation of the DMs' weights is introduced in the following description.

The individual network centrality in a social network is first performed. We use the cut matrix RS_{θ}^{t} of the relationship strength at the t-th stage to simplify the network. The cut matrix RS_{θ}^{t} is defined as follows:

$$RS_{\theta}^{t} = \left(rs_{i,j}^{t}(\theta)\right)_{M\times M}, \quad \text{where } rs_{i,j}^{t}(\theta) = \begin{cases}1, \text{for } rs_{i,j}^{t}\geq\theta,\\ 0, \text{for } rs_{i,j}^{t}<\theta.\end{cases} \tag{8}$$

According to RS_{θ}^{t}, we can construct a new relationship network, in which it only has the directed line from e_i to e_j when $rs_{i,j}^{t}(\theta) = 1$. Therefore, the in-degree and out-degree of nodes from RS_{θ}^{t} can be obtained easily:

(i) In-degree of a node e_i in the simplified relationship network is $I_i = \sum_{j=1}^{M} rs_{j,i}^{t}(\theta) - 1$.

(ii) Out-degree of a node e_i in the simplified relationship network is $O_i = \sum_{j=1}^{M} rs_{i,j}^{t}(\theta) - 1$.

Therefore, the individual network centrality of e_i is denoted as inc_i; that is,

$$inc_i = \frac{I_i + O_i}{2M}. \tag{9}$$

Secondly, the difference between e_i's preference and the collective is defined as follows:

$$d(e_i, C) = \frac{\sum_{p=1}^{P}\sum_{n=1}^{N}\left(Q^{i,t} - Q^{C,t}\right)}{P \cdot N}, \tag{10}$$

where $Q^{C,t} = (\sum_{i=1}^{M} Q^{i,t}/M)$ represents the average collective preference.

Therefore, the weight ω_i of DM e_i can be calculated according to the following equation:

$$\omega_i = \frac{2 - \sin(\pi/2 \cdot d(e_i, C)) + inci_i}{\sum_{i=1}^{M}\left[2 - \sin(\pi/2 \cdot d(e_i, C)) + inci_i\right]}. \tag{11}$$

5. The Decision Process

After obtaining the DMs' cooperative and noncooperative degree and each DM's weights, the decision process should be continued. If the decision results can be obtained for the LSGDM problem, the decision-making process is ended. Otherwise, the adjustment process should be executed to improve the quality of the decision results. The process of obtaining decision results is shown in Section 5.1, and Section 5.2 presents the adjustment process.

5.1. The Calculation of the Decision Results. Based on equation (3), the collective cooperative degree and noncooperative degree can be calculated through the aggregation operator as follows:

$$\text{Collective}_{\omega}(e_1, \ldots, e_M) = < ccd, cnd > = < \sum_{j=1}^{M}\omega_j cd_j, \sum_{j=1}^{M}\omega_j nd_j >. \tag{12}$$

Then, using the score function [33] of intuitionistic fuzzy sets, we can calculate the score for the current cooperation situation:

$$s = ccd - cnd. \tag{13}$$

Suppose that φ is the threshold of the cooperation. The determination of the threshold φ is as follows:

$$\varphi = \overline{cd}(1 - v(cd)) - \overline{nd}(1 - v(nd)), \tag{14}$$

where $\overline{cd} = (\sum_{m=1}^{M} cd_m/M)$ and $\overline{nd} = (\sum_{m=1}^{M} nd_m/M)$ represent the mean of the cooperative and noncooperative degree and $v(cd) = \sqrt{(1/M)\sum_{m=1}^{M}(cd_m - \overline{cd})^2}$ and $v(nd) = \sqrt{(1/M)\sum_{m=1}^{M}(nd_m - \overline{nd})^2}$ represent the standard deviation of the cooperative and noncooperative degree, respectively.

If $s \geq \varphi$, the current cooperation situation can be accepted, and the decision process should be subsequently ended. The collective preference should be calculated as follows:

$$Q^{c,t} = \left(q_{p,n}^{c,t}\right)_{P\times N} = \sum_{m=1}^{M}\omega_m Q^{m,t}. \tag{15}$$

Then, the collective preference for each alternative can be obtained according to the following equation:

$$Q(xp) = \sum_{n=1}^{N} w_n q_{p,n}^{c,t}, \tag{16}$$

$$FQ(xp) = sQ\left(x_p\right). \tag{17}$$

Therefore, the optimal alternative x_k can be given by $FQ(x_k) = \max\left\{FQ(x_1), \ldots, FQ(x_p)\right\}$ for the LSGDM problem. If $s < \varphi$, the adjustment process should be executed to improve the quality of the decision results.

5.2. The Adjustment Process. The adjustment process aims to improve the quality of the decision results. Therefore, the adjustment process includes two parts: identification and feedback.

5.2.1. Identification Process. This process aims to identify the DM that needs to adjust. The score for each DM should be first calculated based on the following rule:

$$s(e_i) = cd_i - nd_i. \tag{18}$$

A set A is then used to represent the set of the DMs that need to adjust; that is, $A = \{e_i | s(e_i) < \varphi\}$. In this study, DM e_a that needs to modify is denoted as $e_a = \min\{e_i | e_i \in A\}$.

5.2.2. Feedback Process. This process goal is to improve the decision results through the help of several moderators. If a DM becomes the one that needs to adjust, it means that the DM's cooperative degree is lower and the noncooperative degree is greater relatively. In order to enhance the relationship in this network and improve the result, the moderators should communicate with him more to increase this DM's cooperative degree and reduce the noncooperative degree. Most of the existing studies generally are given on adjustment rules based on mathematical analysis. Fewer studies think and advise that the DM should exit the decision-making process [34, 35]. We believe that this is unfair to the DMs and may lead to a wrong decision result. Therefore, in this study, the adjustment strategies are developed as follows. Detailed procedure is given as follows.

5.3. The Framework of the Proposed Model. As mentioned above, we summarize the procedure of the proposed model as follows.

The LSGDM model with cooperative behavior is based on SNA considering propagation of DMs' preference.

Input. The weights of the attributes w_m, the DMs' initial preference information $Q^{m,1}$, and the initial relationship strength matrix RS^1.

Output. The optimal alternative.

Stage 1. The calculation of several variables

Step 1.1. Calculate the DM e_i's cooperative degree cd_i by equation (3).
Step 1.2. Compute the DM e_i's hesitant degree hd_i and noncooperative degree nd_i utilizing equation (5).
Step 1.3. Obtain the weight ω_i for each DM based on equation (11).

Stage 2. The judgment process

Step 2.1. By equation (13), the current score s can be obtained.
Step 2.2. Calculate the decision-making score threshold φ based on equation (14).
Step 2.3. Compare the sizes of s and φ. If $s \geq \varphi$, turn to Step 4.1. Otherwise, turn to the next step.

Stage 3. The adjustment process

Step 3.1. Calculate the score $s(e_i)$ for each DM and identify DM e_a that needs to adjust.
Step 3.2. Based on Algorithm 1, update and obtain the DM e_a's cooperative degree cd_a', hesitant degree hd_a', and noncooperative degree nd_a'.

Stage 4. The collective preference process

Step 4.1. Obtain the final outcomes of cd_i, hd_i, and nd_i for each DM.
Step 4.2. Calculate the collective preference considering all DMs' attitude through equation (16).
Step 4.3. Obtain the ranking of all alternatives and the optimal alternative. End.

For convenience of the reading, we visualize the above procedure, which can be shown in Figure 4.

6. Case Study

In this section, the proposed model in a practical scene is applied to demonstrate that the model is valid in solving the LSGDM problems.

6.1. A Practical Example. Colorful garden is a greening company that can provide green plants and flowers to local residents. The company plans to rent a piece of land in a county in Hebei Province to make a profit for the company. The company considers where to lease the land from the following factors: (a) f_1: lease cost, (b) f_2: number of residents within 5 kilometers, (c) f_3: construction cost, and (d) f_4: other factors. There are four optional locations: (1) a place of about 4000 square meters (about 5 kilometers away from the center of the county); (2) a village of about 8000 square meters outside the county (about 7 kilometers away from this county); (3) a village of about 10000 square meters outside the county (15 kilometers away from this county); (4) a place of less than 800 square meters in the center of the county. In order to ensure the correctness of the decision-making results, 20 decision-making participants join this decision-making process: 5 company heads, 5 relatives of company heads, 8 personnel outside the company (2 residents in each alternative location), and 2 policy interpreters. For example, if a place close to the center of the county is selected, the area will become small, the rental cost will rise, and the passenger flow will also rise. Conversely, when you choose a place far from the center of the county, the area will become larger, the rental cost will rise, and the passenger flow may be reduced. At the same time, it plays a very important role in supporting the internal development of the company. Therefore, it is necessary to choose a satisfactory alternative through group decision-making. The information provided by experts is reported in Appendix.

6.2. Decision-Making Process. The proposed model is applied to obtain an optimal alternative considering the relationship between all DMs. Detailed procedure is given below. Note that $\theta = 0.3$ and $\gamma = 0.2$ in this example.

Stage 1. Input: the information w_m, $Q^{m,1}$, and RS^1 provided by experts is reported in Appendix.

Stage 2. The calculation of several variables: based on equation (3), equation (5), and equation (7), the cooperative degree cd_i, hesitant degree hd_i, and noncooperative degree nd_i for each DM are calculated, as shown in Table 2.

Then, the weight for each DM according to equation (11) is computed as shown in Table 3.

Stage 3. Judgment process: based on the above results, the collective cooperative degree and collective noncooperative degree can be calculated; that is, $s = 0.0919$. Then, the threshold φ should be calculated according to equation (14), as shown in Table 4.

Obviously, $s < \varphi$, and it means the current situation should to adjusted. Therefore, the adjustment process should be executed at the next stage.

Stage 4. Adjustment process: the score $s(e_i)$ for each DM can obtained by equation (17) as shown in Table 5.

Then, DM e_{15} is identified to enter the adjustment process. Based on Algorithm 1, the adjustment values of cd_{15}', hd_{15}', and nd_{15}' are 0.2502, 0.4392, and 0.3106, respectively. Subsequently, the adjusted collective score is 0.0969. The current result is also not satisfactory. The second adjustment should be executed. At the second stage, DM e_8 should be adjusted, and the adjustment values of cd_8', hd_8', and nd_8' are 0.2649, 0.4063, and 0.3288, respectively. The adjusted collective score at the second stage is 0.1010. The current result cannot be accepted. The third adjustment should be executed. At the third stage, DM e_2 should be adjusted, and the adjustment values of cd_2', hd_2', and nd_2' are 0.2645, 0.4138, and 0.3217, respectively. The adjusted collective score at the third stage is 0.1049. The current result cannot be accepted. The fourth adjustment should be executed. At the 4-th stage, DM e_3 should be adjusted, and the adjustment values of cd_3', hd_3', and nd_3' are 0.2603, 0.4362, and 0.3035, respectively. The adjusted collective score at the 4-th stage is 0.1091. The current result is also not satisfactory. The next adjustment should be executed. At the 5-th stage,

Input: the numbers of cd_a, hd_a, and nd_a.
Output: the adjustment values of cd_a', hd_a', and nd_a'.
Step 1. Obtain the cooperative degree cd_a, hesitant degree hd_a, and noncooperative degree nd_a of the DM e_a. Then, the sum of cd_a and nd_a is compared with hd_a.
Step 2. If $cd_a + nd_a < hd_a$, it means that the DM's hesitant degree is higher. Turn to Step 3; otherwise, turn to Step 5.
Step 3. If $cd_a \geq nd_a$, it means that this DM needs to improve his cooperative behavior. The method of decreasing the hesitant degree can be used. Then, we set $cd_a = cd_a + \gamma\ hd_a$. Else, turn to Step 4.
Step 4. If $cd_a < nd_a$, it means that this DM's cooperative degree is lower and noncooperative degree is higher. Then, we set $cd_a = cd_a + \gamma\ hd_a$ and $hd_a = hd_a + \gamma\ nd_a$. Turn to Step 6.
Step 5. If $cd_a + nd_a \geq hd_a$ and the score of this DM is still lower, it means the noncooperative degree is larger than the cooperative degree. Therefore, the cooperative degree and the hesitant degree should be adjusted. We set $cd_a = cd_a + \gamma\ hd_a$ and $hd_a = hd_a + \gamma\ nd_a$.
Step 6. After adjusting the cooperative degree, the hesitant degree, and the noncooperative degree, the normalized process should be executed. Detailed procedure is given as follows: $cd_a' = (cd_a/(cd_a + hd_a + nd_a))$, $hd_a' = (hd_a/(cd_a + hd_a + nd_a))$, and $nd_a' = (nd_a/(cd_a + hd_a + nd_a))$.
Step 7. Output the adjustment number of cd_a', hd_a', and nd_a'. End.

ALGORITHM 1: The increase of cooperative and the decrease of noncooperative degree.

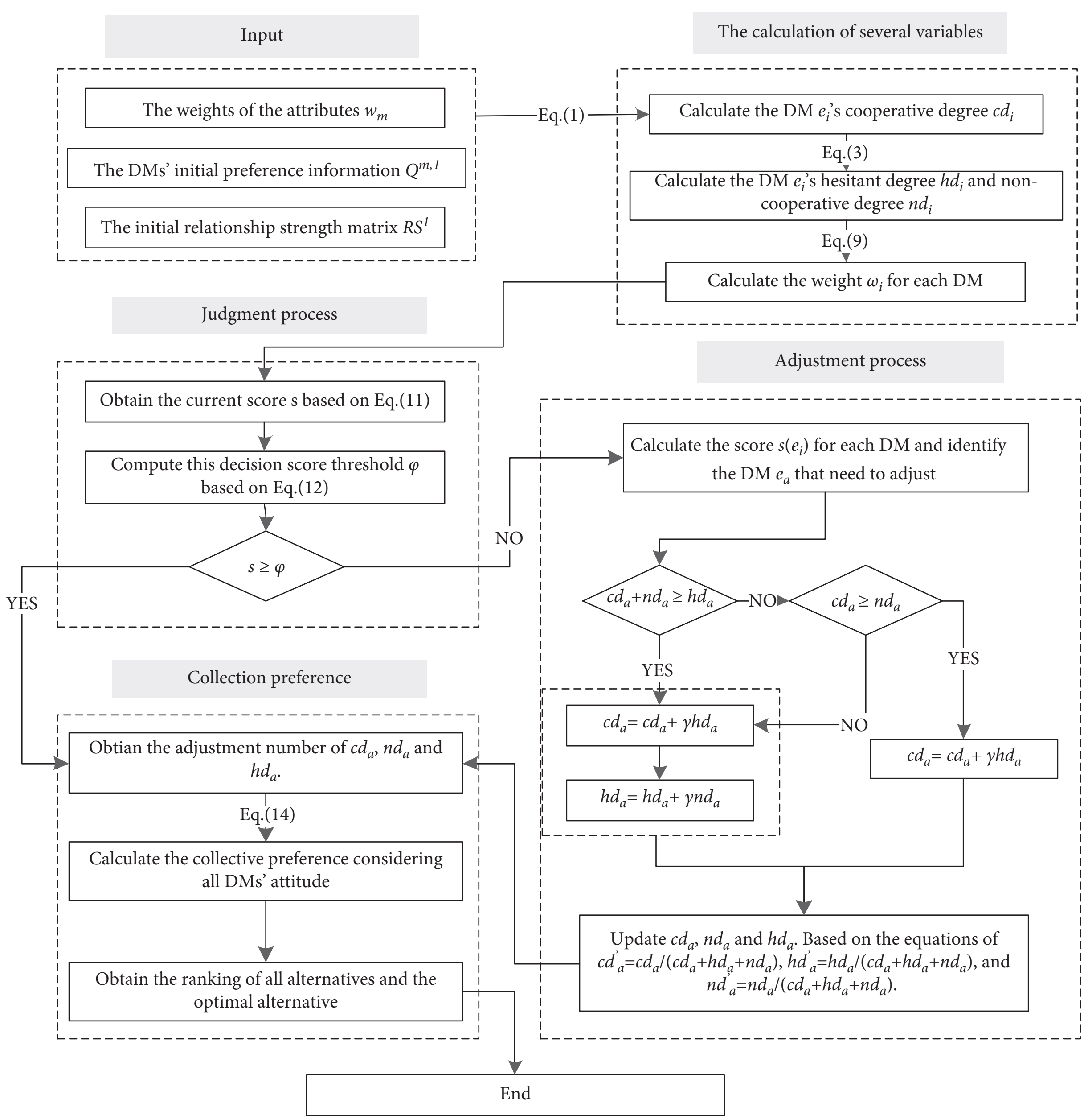


FIGURE 4: The visualization of the LSGDM model with cooperative behavior based on SNA considering propagation of DMs' preference.

Table 2: The values of cd_i, hd_{ii}, and nd_i after the calculation process.

i	1	2	3	4	5	6	7	8	9	10
cd_i	0.4794	0.2248	0.2143	0.2718	0.2594	0.4038	0.226	0.2272	0.3278	0.3805
hd_i	0.3665	0.4036	0.4345	0.5174	0.408	0.4043	0.4057	0.3932	0.3861	0.4791
nd_i	0.1541	0.3716	0.3512	0.2109	0.3326	0.1919	0.3683	0.3796	0.2861	0.1404
i	11	12	13	14	15	16	17	18	19	20
cd_i	0.342	0.3238	0.439	0.2941	0.2026	0.4737	0.3688	0.3307	0.5444	0.317
hd_i	0.542	0.4533	0.378	0.4002	0.4373	0.4231	0.4531	0.4382	0.2626	0.419
nd_i	0.116	0.2229	0.183	0.3057	0.3601	0.1032	0.1781	0.2311	0.193	0.264

Table 3: The weights of the DMs.

j	1	2	3	4	5	6	7	8	9	10
w_j	0.042	0.044	0.0443	0.0473	0.0479	0.0435	0.0503	0.0463	0.0522	0.0507
i	11	12	13	14	15	16	17	18	19	20
w_j	0.056	0.0453	0.0524	0.0517	0.0521	0.0579	0.0584	0.0504	0.0565	0.051

Table 4: Preparation before threshold calculation.

	$\overline{cd}$	$v(cd)$	$\overline{nd}$	$v(nd)$	φ
Value	0.4326	0.0980	0.3063	0.0915	0.1119

DM e_7 should be adjusted, and the adjustment values of cd_7', hd_7', and nd_7' are 0.2659, 0.4151, and 0.3189, respectively. The adjusted collective score at the 5-th stage is 0.1136. Apparently, the result of this stage can be accepted.

Stage 5. The preference collection: after the 5-th adjustment process, the current situation can be accepted. The preference collection process should be then executed based on equation (15) as follows:

$$Q^{C,5} = \left(q_{p,n}^{c,5}\right)_{P\times N} = \begin{pmatrix} 0.4308 & 0.4077 & 0.5293 & 0.5594 \\ 0.5207 & 0.5490 & 0.5071 & 0.5524 \\ 0.6123 & 0.5143 & 0.6560 & 0.7243 \\ 0.5697 & 0.4953 & 0.6480 & 0.4334 \end{pmatrix}. \quad (19)$$

Then, the collective preference for each alternative considering all DMs' attitude should be calculated by equation (16) and equation (17), as shown in Table 6.

Finally, the ranking of the alternative is $x_3 \succ x_4 \succ x_2 \succ x_1$, and the optimal alternative is x_3.

6.3. Comparable Analysis. This section aims to present the superiority of our proposed model by comparing the results with other similar studies. Since the context of existing studies has differences, comparative studies will calculate decision-making results by using some of their innovative approaches, which are related to our proposed model. The details are as follows:

(a) Liu et al. [17] proposed a conflict detection and elimination model based on SNA, which considers the multipath propagation of the DM's trust relationship. Replacing the propagation of DMs' preference proposed in this study with Liu et al.'s multipath trust relationship propagation, the collective preference for each alternative can be obtained as $Q(x_1) = 0.4894$, $Q(x_2) = 0.5009$, $Q(x_3) = 0.5413$, and $Q(x_4) = 0.5105$. And the collective preference for each alternative considering all DMs' attitude is subsequently calculated by equation (17). That is, $FQ(x_1) = 0.0556$, $FQ(x_2) = 0.0569$, $FQ(x_3) = 0.0615$, and $FQ(x_4) = 0.0580$. Obviously, the ranking of the alternative is $x_3 \succ x_4 \succ x_2 \succ x_1$, and the optimal alternative is x_3. Such a result is the same as our research's result. Moreover, $0.0698 > 0.0615$. Therefore, our results are not only scientific but better than Liu et al.'s research calculations. The comparison results are shown in Figure 5.

(b) Zhang et al. [31] focused on the noncooperative behaviors. In their model, the social network and expert weights are dynamically updated. In the process of comparing with Zhang et al.'s model, we keep the social network unchanged and keep the DMs' preference propagated, and the weight determination is calculated by the proposed method of our study. The collective preference for each alternative considering all DMs' attitude can be obtained as $FQ(x_1) = 0.0567$, $FQ(x_2) = 0.0621$, $FQ(x_3) = 0.0692$, and $FQ(x_4) = 0.0665$. Obviously, the ranking of the alternative is $x_3 \succ x_4 \succ x_2 \succ x_1$, and the optimal alternative is also x_3. Such ranking is the same as our research. And, the calculation result of our research is better. The comparison results are shown in Figure 5.

(c) Ding et al. [6] proposed a conflict relationship investigation process based on SNA to detect conflict between DMs in LSGDM events. The difference between the defining method of the noncooperation degree in our research and Ding et al.'s research is that we take the DM's position in a social network

Table 5: The score $s(e_i)$ for each DM.

i	1	2	3	4	5	6	7	8	9	10
$s(e_i)$	0.3253	−0.1470	−0.1370	0.0610	−0.0730	0.2119	−0.1420	−0.1520	0.0417	0.2401
i	11	12	13	14	15	16	17	18	19	20
$s(e_i)$	0.2270	0.1009	0.2560	−0.0120	−0.1570	0.3705	0.1907	0.0996	0.3514	0.0530

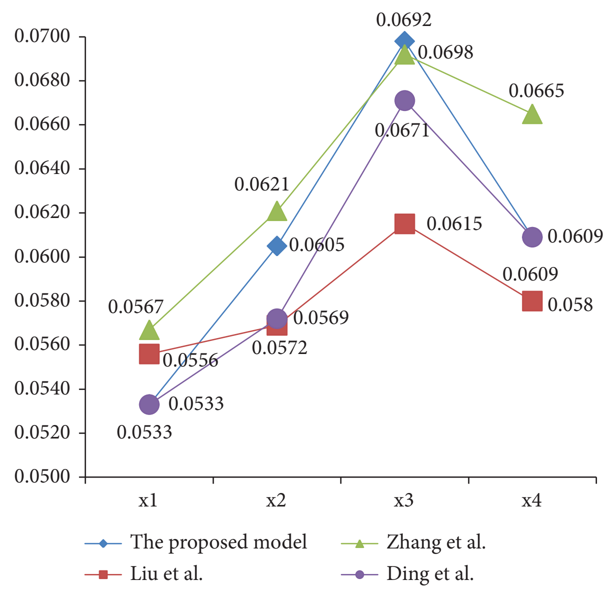


Figure 5: The differences between our proposed model and existing studies.

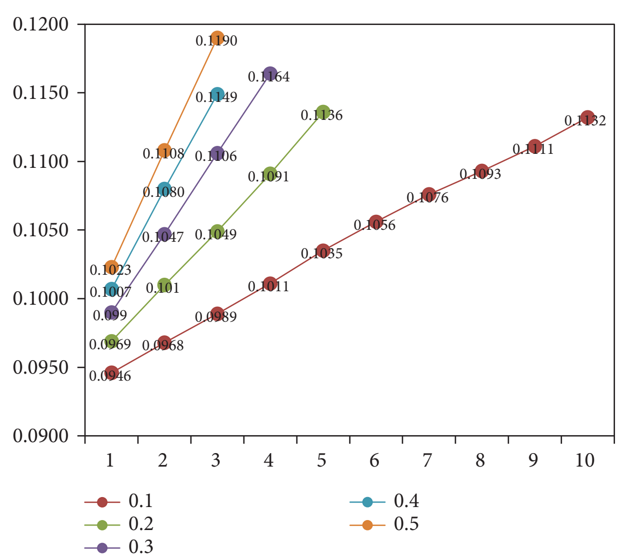


Figure 6: The adjustment times and the adjusted score under the different γ.

and his own opinion and attitude more into account. Using Ding et al.'s proposed model, we can calculate the collective preference for each alternative considering all DMs' attitude: $FQ(x_1) = 0.0533$, $FQ(x_2) = 0.0572$, $FQ(x_3) = 0.0671$, and $FQ(x_4) = 0.0564$. The ranking of the alternative is x_3 $x_3 \succ x_2 \succ x_1$, and the optimal alternative is also x_4. Such the optimal alternative is the same as our research, but the ranking is slightly different. This may be because we take into account both his position in the network and his own opinion and attitude.

According to Figure 5, we found that the optimal alternative is the same, and the ranking is generally the same. This indicates that our proposed model is valid and stable for the practical LSGDM problems. Moreover, the score of our proposed model is greater than that of other models, which suggests that our model has a high superiority through the

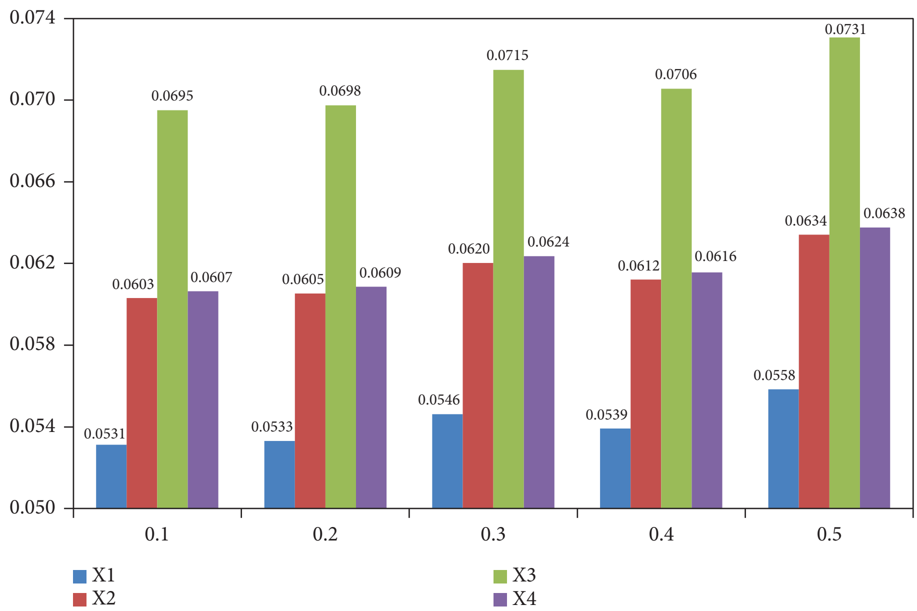


Figure 7: The collective preference of the alternatives with different γ.

Table 6: The collective alternative preference.

i	1	2	3	4
$Q(x_i)$	0.4693	0.5328	0.6140	0.5358
$FQ(x_i)$	0.0533	0.0605	0.0698	0.0609

Table 7: The preference information $Q^{m,1} = (q_{pn}^{m,1})_{P\times N}$ $(m = 1,\ldots,20)$ for each DM.

		$f1$	$f2$	$f3$	$f4$		$f1$	$f2$	$f3$	$f4$		$f1$	$f2$	$f3$	$f4$		$f1$	$f2$	$f3$	$f4$
$x1$		0.2	0.2	0.6	0.8		0.4	0.5	0.4	0.7		0.4	0.5	0.6	0.6		0.4	0.5	0.4	0.4
$x2$	$e1$	0.1	0.5	0.8	0	$e2$	0.9	0.1	0.5	0.2	$e3$	0.7	1.0	0.4	0.9	$e4$	0.9	0.2	0.3	0.7
$x3$		0.5	0.2	0.9	1.0		0.7	0.8	0.8	1.0		0.4	0.5	0.5	0.8		0.7	0.5	0.3	0.4
$x4$		0.9	0.1	1.0	1.0		0.5	0.6	0.5	0.2		0	0.9	0.6	0.8		0.3	0.2	0.5	0
$x1$		0.4	0.6	0.4	0.2		0.6	0.2	0.9	0.5		0.6	0.7	0.6	0.5		0.3	0.4	0.9	0.7
$x2$	$e5$	0.5	0.9	0.3	0.4	$e6$	0.6	0.5	0.5	0.2	$e7$	0.9	0.9	0.4	0.3	$e8$	0.4	0.5	0.5	0.2
$x3$		0.5	0.8	0.5	0.5		0.7	0.2	0.6	0		0.8	0.6	0.5	0.9		0.2	0.7	0.6	0.8
$x4$		0.2	0.8	0.6	0.5		0.3	0.1	1.0	0.9		0.8	0.5	0.6	0.4		0.9	0.5	1.0	0.5
$x1$		0.4	0.3	0.3	1.0		0.2	0.3	0.4	0.6		0.7	0.2	0.4	0.5		0.8	0.3	0.6	0.4
$x2$	$e9$	0	0.6	0.6	0.5	$e10$	0.1	0.4	0.5	0.9	$e11$	0.9	0.4	0.5	0.3	$e12$	0	0.6	0.4	0.9
$x3$		0.7	0.2	0.8	0.5		0.5	0.2	0.8	0.8		0.8	0.8	0.7	1.0		1.0	0.4	0.8	0.7
$x4$		0.5	0.4	0.5	0.1		0.9	0.9	0.5	0.8		0.5	0.4	0.6	0.4		1.0	0	0.9	0.3
$x1$		0.4	0.4	0.7	0.4		0.7	0.2	0.4	0.3		0.4	0.6	0.3	0.4		0.2	0.5	0.6	0.4
$x2$	$e13$	0.9	0.1	0.5	1.0	$e14$	0.4	0.4	0.5	0.6	$e15$	0.6	0.6	0.6	1.0	$e16$	0.5	0.8	0.8	0.9
$x3$		0.7	0.8	0.6	0.7		0.8	0.6	0.3	0.4		0.7	0.4	0.8	0.9		0.5	0.8	0.9	0.7
$x4$		0.5	0.6	0.2	0.3		0.5	0.4	0.5	0.1		0.2	0.5	0.5	0.5		0.6	0.6	1.0	0.3
$x1$		0.6	0.7	0.6	0.5		0.3	0.4	0.9	0.7		0.4	0.3	0.3	1.0		0.2	0.3	0.4	0.6
$x2$	$e17$	0.9	0.9	0.4	0.3	$e18$	0.4	0.5	0.5	0.2	$e19$	0.5	0.6	0.6	0.5	$e20$	0.1	0.4	0.5	0.9
$x3$		0.8	0.6	0.5	0.9		0.2	0.7	0.6	0.8		0.5	0.2	0.8	0.5		0.5	0.2	0.8	0.8
$x4$		0.8	0.5	0.6	0.4		0.9	0.5	1.0	0.5		0.2	0.4	0.5	0.1		0.9	0.9	0.5	0.8

score calculation of the value of the optimal solution. It further demonstrates that the proposed model considering the network status and the preference for each DM is superior.

6.4. Sensitivity Analysis. In this practical case, the final decision-making results are obtained after five adjustments. The adjusted parameter $\gamma = 0.2$ in this example. In this subsection, a discussion based on the different adjusted parameter is introduced. To further prove the stability of the proposed consensus model, a sensitivity analysis is conducted with different values of $\gamma = \{0.1, 0.2, 0.3, 0.4, 0.5\}$. The adjustment times and the adjusted score and the collective preference of the alternatives with different γ are recorded in Figures 6 and 7, respectively.

Table 8: The relationship strength RS^1 between DMs.

$\longrightarrow$	e_1	e_2	e_3	e_4	e_5	e_6	e_7	e_8	e_9	e_{10}	e_{11}	e_{12}	e_{13}	e_{14}	e_{15}	e_{16}	e_{17}	e_{18}	e_{19}	e_{20}
e_1	1.0	0	0.4	0.2	0.6	0.7	0	0.1	0	0	0.5	0.9	0.6	0	0.3	0.6	0.2	0	0.9	0
e_2	0	1.0	0	0.5	0.4	0.5	0.1	0	0.3	0.1	0	0.3	0.2	0	0.2	0	0.2	0.7	0.2	0.2
e_3	0.6	0	0.1	0.1	0.5	0.2	0	0.1	0.7	0	0.5	0.1	0	0.2	0.5	0.5	0.2	0.1	0	0.5
e_4	0.4	0.2	0.8	1.0	0.2	0.1	0.3	0.2	0.3	0.6	0	0.2	0.7	0.3	0	0.2	0.1	0.8	0.3	0.2
e_5	0.4	0.4	0.2	0	1.0	0.2	0.2	0	0.7	0	0	0.2	0.5	0.2	0.3	0	0.5	0.2	0.2	0
e_6	0.9	0	0.2	0.8	0	1.0	0.2	0.2	0.5	0.1	0.3	0.8	0	0.3	0.5	0.3	0	0.2	0.8	0.7
e_7	0	0.3	0.3	0.5	0.3	0	1.0	0.2	0.1	0.1	0.5	0.3	0	0.3	0	0.2	0.4	0.3	0	0.3
e_8	0.1	0	0.3	0	0.4	0.3	0	1.0	0.2	0.3	0	0.2	0.5	0.3	0.3	0	0	0.3	0.2	0.4
e_9	0	0.5	0	0.3	0.4	0	0.4	0.3	1.0	0.3	0	0	0.2	0	0.2	0.3	0.5	0	0.7	0.3
e_{10}	0	0.3	0.8	0.7	0.2	0.3	0.7	0.3	0.2	1.0	0.3	0.2	0	0.3	0.8	0.3	0.3	0	0.8	0.3
e_{11}	0.3	0	0.2	0.3	0.8	0.3	0.3	0.7	0.3	0.2	1.0	0.2	0.3	0.2	0.3	0.8	0.3	0.5	0.3	0.8
e_{12}	0.8	0.2	0.1	0	0.4	0.2	0.4	0	0.8	0.2	0.1	1.0	1.0	0.1	0.8	0.3	0.4	0.3	0.4	0.3
e_{13}	0.6	0.3	0.8	0.3	0	0.2	0.8	0.3	0.8	0.7	0.3	0.2	0.3	0.8	0.2	0.3	0.8	0.6	0.2	0.8
e_{14}	0	0	0.3	0.8	0.3	0.5	0	0.1	0.3	0.3	0.2	0.3	0	1.0	0.3	0.8	0.3	0.2	0	0.3
e_{15}	0.2	0.3	0.8	0	0.2	0.1	0.2	0.2	0.2	0.3	0.5	0.2	0.2	0.3	1.0	0.3	0.3	0	0.2	0.3
e_{16}	0.5	0	0.8	0.2	0.8	0	0.2	0.5	0.3	0.7	0.8	0.3	0.3	0.8	0.3	1.0	0.3	0.5	0.2	0.9
e_{17}	0.5	0.4	0.3	0	0.3	0.4	0.3	0.3	0.7	0.3	0.7	0	0.5	0.4	0.3	0.3	1.0	0.2	0.5	0.3
e_{18}	0	0.3	0	0.3	0.7	0.3	0.8	0.1	0	0.1	0.7	0.3	0.1	0.2	0.8	0.3	0.3	1.0	0.3	0.7
e_{19}	0.8	0.8	0.7	0.3	0.8	0	0.3	0.2	0.8	0.3	0.7	0.8	0.3	0.3	0.8	0.8	0.3	0.1	1.0	0.8
e_{20}	0	0.2	0.1	0.8	0	0.1	0.8	0.4	0.3	0.4	0.2	0	0	0.8	0.2	0.6	0	0.2	0.3	1.0

Table 9: The weights for each attribute.

Attributes	f_1	f_2	f_3	f_4
w_j	0.3	0.3	0.2	0.2

In Figure 6, the number of the adjustment is 4 when $\gamma = 0.4$ and $\gamma = 0.5$. The number of the adjustment is 5 when $\gamma = 0.2$ and $\gamma = 0.3$. And the number of the adjustment is 10 when $\gamma = 0.1$. This is because as the value of γ increases, the adjustment speed also increases, and the speed of the accepted decision results also increases. In Figure 7, the result is the same that $x_3 \succ x_4 \succ x_1 \succ x_2$ when the number of γ is different. This is because the final collective preference reflects the level of support of DMs. Therefore, the results indicate that the proposed model is stable and the number of γ is relatively reasonable in the decision-making process.

7. Conclusion

In this study, a large-scale group decision-making model with cooperative behavior based on social network analysis considering the propagation of DMs' preference is proposed and applied to select the location problem of a garden company. Our proposed model in this study gives a new perspective from the relationship and the cooperative behaviors of DMs in LSGDM problems. The main contributions of this research are as follows. Firstly, a novel calculation method of cooperative degree, hesitant degree, and noncooperative degree for each DM is developed. Such a method not only considers the network status but also considers the preference information for each DM, and thereby it can better represent the current state for each DM. Then, our research performs a new determination method of each DM considering both the individual network centrality and preference similarity degree, which can make the weight of DMs fairer, and it is also conducive to promoting a more stable relationship between DMs. Subsequently, the score for the current cooperation situation is given, and the improvement algorithm of the increase of cooperative degree and the decrease of noncooperative degree is designed to enhance the quality of the decision-making results. In addition, the collective preference considering all DMs' attitude is conducted to obtain the optimal choice. Finally, our proposed model has demonstrated scientificity, rationality, superiority, and stability through a practical case and comparative and sensitive analysis.

Meanwhile, there remain some limitations of this research that should be further dealt with in the future. In our research, in addition to the cooperation behavior of the proposed model, the professional knowledge background and decision-making experience and other individual attributes of DMs should be considered. Moreover, the large-scale group decision-making model considering the psychological factor (i.e., self-confident) of DMs will be a meaningful research for the LSGDM problems.

Appendix

The information provided by participants is reported in Tables 7–9. In this study, the value range of q^m_{pn} is from 0 to 1.

Data Availability

The data used to support the findings of this paper are included within the article (Case Study section and Appendix).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

The authors appreciate the financial support of the National Key Research and Development Program of China (Grant no. 2018YFB1402500) and the Natural Science Foundation of Heilongjiang Province (Grant no. JJ2021LH1530).

References

[1] J. Chu, Y. Wang, X. Liu, and Y. Liu, "Social network community analysis based large-scale group decision making approach with incomplete fuzzy preference relations," *Information Fusion*, vol. 60, pp. 98–120, 2020.

[2] S. Li and C. Wei, "A large scale group decision making approach in healthcare service based on sub-group weighting model and hesitant fuzzy linguistic information," *Computers & Industrial Engineering*, vol. 144, Article ID 106444, 2020.

[3] Y. Liu, Z.-P. Fan, and X. Zhang, "A method for large group decision-making based on evaluation information provided by participators from multiple groups," *Information Fusion*, vol. 29, pp. 132–141, 2016.

[4] X. Xu, Q. Zhang, and X. Chen, "Consensus-based non-cooperative behaviors management in large-group emergency decision-making considering experts' trust relations and preference risks," *Knowledge-Based Systems*, vol. 190, Article ID 105108, 2020.

[5] X.-H. Xu, Z.-J. Du, and X.-H. Chen, "Consensus model for multi-criteria large-group emergency decision making considering non-cooperative behaviors and minority opinions," *Decision Support Systems*, vol. 79, pp. 150–160, 2015.

[6] R.-X. Ding, X. Wang, K. Shang, and F. Herrera, "Social network analysis-based conflict relationship investigation and conflict degree-based consensus reaching process for large scale decision making using sparse representation," *Information Fusion*, vol. 50, pp. 251–272, 2019.

[7] D. García-Zamora, A. Labella, W. Ding, R. M. Rodríguez, and L. Martínez, "Large-scale group decision making: a systematic review and a critical analysis," *IEEE/CAA Journal of Automatica Sinica*, vol. 9, no. 6, pp. 949–966, 2022.

[8] I. P. Carrascosa, *Large Group Decision Making: Creating Decision Support Approaches at Scale*, Springer, Berlin, Germany, 2018.

[9] X. Xu, X. Yin, and X. Chen, "A large-group emergency risk decision method based on data mining of public attribute preferences," *Knowledge-Based Systems*, vol. 163, pp. 495–509, 2019.

[10] Y. Dong, S. Zhao, H. Zhang, F. Chiclana, and E. Herrera-Viedma, "A self-management mechanism for noncooperative behaviors in large-scale group consensus reaching processes," *IEEE Transactions on Fuzzy Systems*, vol. 26, no. 6, pp. 3276–3288, 2018.

[11] X.-H. Xu, Z.-J. Du, X.-H. Chen, and C.-G. Cai, "Confidence consensus-based model for large-scale group decision making: a novel approach to managing non-cooperative behaviors," *Information Sciences*, vol. 477, pp. 410–427, 2019.

[12] I. Palomares, L. Martínez, and F. Herrera, "MENTOR: a graphical monitoring tool of preferences evolution in large-scale group decision making," *Knowledge-Based Systems*, vol. 58, pp. 66–74, 2014.

[13] & J. Zhan, "Secure collaborative social networks," *IEEE Transactions on Systems, Man and Cybernetics, Part C. Applications and Reviews*, vol. 40, 2010.

[14] E. Bakshy, I. Rosenn, C. Marlow, and L. Adamic, "The role of social networks in information diffusion," in *Proceedings of the 21st International Conference*, New York, NY, USA, February 2012.

[15] S. Hill, F. Provost, and C. Volinsky, "Network-based marketing: identifying likely adopters via consumer networks," *Statistical Science*, vol. 21, no. 2, pp. 256–276, 2006.

[16] X.-H. Xu and Z.-X. Yu, "A large group emergency decision making method and application based on attribute mining of public behaviour big data in social network environment," *Control and Decision*, vol. 37, no. 1, pp. 1–10.

[17] B. Liu, Q. Zhou, R.-X. Ding, I. Palomares, and F. Herrera, "Large-scale group decision making model based on social network analysis: trust relationship-based conflict detection and elimination," *European Journal of Operational Research*, vol. 275, no. 2, pp. 737–754, 2019.

[18] Z. Zhang and Z. Li, "Personalized individual semantics-based consistency control and consensus reaching in linguistic group decision making," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, pp. 1–13, 2021.

[19] Y. Gao and Z. Zhang, "Consensus reaching with non-cooperative behavior management for personalized individual semantics-based social network group decision making," *Journal of the Operational Research Society*, pp. 1–18, 2021.

[20] Z. Zhang, Z. Li, and Y. Gao, "Consensus reaching for group decision making with multi-granular unbalanced linguistic information: a bounded confidence and minimum adjustment-based approach," *Information Fusion*, vol. 74, pp. 96–110, 2021.

[21] Z.-S. Chen, X.-L. Liu, K.-S. Chin, W. Pedrycz, K.-L. Tsui, and M. J. Skibniewski, "Online-review analysis based large-scale group decision-making for determining passenger demands and evaluating passenger satisfaction: case study of high-speed rail system in China," *Information Fusion*, vol. 69, pp. 22–39, 2021.

[22] L. Xiao, Z.-S. Chen, X. Zhang, J.-P. Chang, W. Pedrycz, and K.-S. Chin, "Bid evaluation for major construction projects under large-scale group decision-making environment and characterized expertise levels," *International Journal of Computational Intelligence Systems*, vol. 13, no. 1, p. 1227, 2020.

[23] K. T. Atanassov, *Intuitionistic Fuzzy Sets*, Springer Physica-Verlag, Heidelberg, Germany, 1999.

[24] J. Wu, F. Chiclana, H. Fujita, and E. Herrera-Viedma, "A visual interaction consensus model for social network group decision making with trust propagation," *Knowledge-Based Systems*, vol. 122, pp. 39–50, 2017.

[25] J. Wu, L. Dai, F. Chiclana, H. Fujita, and E. Herrera-Viedma, "A minimum adjustment cost feedback mechanism based consensus model for group decision making under social network with distributed linguistic trust," *Information Fusion*, vol. 41, pp. 232–242, 2018.

[26] S. Wasserman, K. Faust, and C. U. Press, *Social Network Analysis: Methods and Applications*, Cambridge University Press, Cambridge, UK, 1994.

[27] P. J. Carrington, J. Scott, and S. Wasserman, *Models and Methods in Social Network Analysis*, Cambridge University Press, Cambridge, UK, 2005.

[28] Y. Liu, C. Liang, F. Chiclana, and J. Wu, "A knowledge coverage-based trust propagation for recommendation mechanism in social network group decision making," *Applied Soft Computing*, vol. 101, Article ID 107005, 2021.

[29] I. Palomares, L. Martinez, and F. Herrera, "A consensus model to detect and manage noncooperative behaviors in large-scale group decision making," *IEEE Transactions on Fuzzy Systems*, vol. 22, no. 3, pp. 516–530, 2014.

[30] X. Li, H. Liao, and Z. Wen, "A consensus model to manage the non-cooperative behaviors of individuals in uncertain group decision making problems during the COVID-19 outbreak," *Applied Soft Computing*, vol. 99, Article ID 106879, 2021.

[31] H. Zhang, I. Palomares, Y. Dong, and W. Wang, "Managing non-cooperative behaviors in consensus-based multiple attribute group decision making: an approach based on social network analysis," *Knowledge-Based Systems*, vol. 162, pp. 29–45, 2018.

[32] Y. Dong, Y. Fan, H. Liang, F. Chiclana, and E. Herrera-Viedma, "Preference evolution with deceptive interactions and heterogeneous trust in bounded confidence model: a simulation analysis," *Knowledge-Based Systems*, vol. 175, pp. 87–95, 2019.

[33] V. Torra, "Hesitant fuzzy sets," *International Journal of Intelligent Systems*, vol. 25, no. 6, pp. 529–539, 2010.

[34] X. H. Xu, X. Y. Zhong, X. H. Chen, and Y. J. Zhou, "A dynamical consensus method based on exit–delegation mechanism for large group emergency decision making," *Knowledge-Based Systems*, vol. 86, pp. 237–249, 2015.

[35] X.-H. Xu, X.-X. Zhong, and Y.-J. Zhou, "Emergency larger group decision method based on exit-commission dynamic conflict elimination mechanism," *Control and Decision*, vol. 30, no. 9, p. 8, 2015.