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A Two-Stage Optimization Model for Large-Scale Group Decision-Making in Disaster Management: Minimizing Group Conflict and Maximizing Individual Satisfaction

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Abstract

As for large-scale group decision-making (LSGDM) in disaster management, the number of decision makers is so large-scale that decision-making is time consuming, but sometimes disaster management is urgent for time. Inspired by multiplayer game theories, this paper proposes a two-stage optimization model that maximizes individual satisfaction at the first stage and minimizes group conflict at the second stage. Furthermore, the introduction of public social media data to determine decision criteria and weights greatly improves the objectivity of decision-making. The proposed method effectively saves the decision time while ensuring the quality of LSGDM. The case study verifies the feasibility of the method.

Keywords Large-scale group decision making · Optimization model · Disaster management · Group conflict · Social media

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1 Introduction

In recent years, various natural or man-made disasters occurred one after another with an uptrend in China, which have brought enormous economic loss and serious social problems (Xu et al. 2015b). Thus, the emergency management of these disasters has drawn great attention of Chinese government, the ministry of emergency management was established in April 2018 to deal with emergency events. Emergency decision-making is a pivotal mode in disaster management and can be treated as a dynamic multicriteria group decision-making problem (Cosgrave 1996; Hao et al. 2018). However, different from the general group decision-making problems, the decision-making for disasters has characteristics of incomplete and unreliable decision-relevant information, the heterogeneity of decision makers, the complex and changeable decision-making environment, ill-defined goals, short-time period, etc. Among them, short-time period is one of the prominent features (Xu et al. 2015c, d; Hao et al. 2018). Taking “8.12 Tianjin Binhai New Area Explosion” accident as an example (Anjianzongju 2016), at 22:51:46 on August 12, one warehouse was on fire; at 23:34:06 at the same day, the first explosion happened. The time between two sub-incidents was less than 18 minutes.

In actual disaster decision-making practice, large-scale group decision-making (LSGDM) is inevitable. The more serious the problem is, the more difficult it is to bear the losses caused by mistakes in decision-making, people are more inclined to choose to involve more decision makers in decision-making. As a result, many government departments and civil organizations, experts and managers in different fields will participate in decision-making. LSGDM refers to the selection of the best satisfactory alternatives from a set of feasible alternatives, predicated on the preferences of a large numbers of decision makers (Liu et al. 2019). When the number of decision makers exceeds 20, the traditional group decision-making problems become LSGDM problems (Chen 2009; Liu et al. 2014b; Zhang et al. 2018). LSGDM problems solving method usually consists of four steps: (1) Normalize original individual decision matrices, (2) Cluster the normalized individual decision matrices, (3) Aggregate the clusters’ decision matrices, (4) Select the best alternatives (Xu et al. 2015c). Recent years, LSGDM problems have attracted the sights of many scholars (Dong et al. 2018; Wang et al. 2019; Liu et al. 2019; Ding et al. 2019). According to the general decision-making process, the existing research mainly innovates from four aspects: different decision maker preference information expressions (Xu et al. 2015a; Zhang et al. 2017; Zhou et al. 2017; Liu et al. 2018; Zuo et al. 2019), attribute weight determination methods (Dong et al. 2016; Liu et al. 2017; Xu et al. 2017; Zhao et al. 2019), large-scale group clustering methods (Liu et al. 2014b; Zhu et al. 2016; Benítez et al. 2018; Ma et al. 2019), and large group preference information aggregation methods (Liu et al. 2014a, 2015; Xu et al. 2018). Among them, large-scale group preference information aggregation is a popular research direction.

As the number of decision makers increases, large-scale group preference information aggregation problem of LSGDM inevitably faces some problems, mainly focusing on two aspects: on one hand, more decision makers means more heterogeneous preferences, it's difficult to eliminate conflicts among decision makers and effectively aggregate large-scale group member's preferences. On the other hand, more decision makers increase the complexity of decision-making and some times brawls caused by conflicts increase decision time of LSGDM. Current research regarding LSGDM focuses on how to achieve group consensus (Gou et al. 2018; Xu et al. 2019c; Liu et al. 2019). Labella et al. (2018) divided these methods of LSGDM into two classes based on consensus progress procedures: LSGDM models with feedback mechanism (Herrera-Viedma et al. 2002; Chiclana et al. 2008; Xu et al. 2015d, c; Li et al. 2019) and LSGDM models without a feedback mechanism (Zhang et al. 2012; Wu and Xu 2012; Xu et al. 2013). LSGDM models without a feedback mechanism can quickly obtain the decision result, but the satisfaction of decision makers or decision quality are not so high. LSGDM models with feedback mechanism have the advantages of ensuring satisfaction of decision makers and large-scale group's decision quality, however, they need more time to achieve a final decision. Time cost of discussing and modifying opinions not only increase the decision time of LSGDM, but also lead to a result that some experts lose their motivation, abandon the discussion process and give up their valuable original preferences; the decision-making may be caught in endless quarrel and can't achieve a group consensus in extreme cases. Furthermore, it should be noticed that people working in groups tend to expend less effort than working as individuals, with large groups exhibiting more "social loafing" (Karau and Williams 1993). There is "a problem of prevention" in that decision risk is increasing as a result of reduced care due to excessive decision makers (Benoit and Dubra 2013).

As for applying public social media data to disaster management, most of the research focuses on disaster early warning (Chatfield et al. 2013; Pohl et al. 2016; Wang et al. 2016), real-time monitoring of disaster situation (Sakaki et al. 2013; Choi and Bae 2015; Xiao et al. 2018), and public opinion analysis (Signorini et al. 2011; Woo et al. 2015; Li et al. 2016). And a small part of the research focuses on decision-making criteria extraction, for example, Xu et al. (2019a, 2019b) take the public opinions related to emergency events into consideration during the decision process, the public opinions are regarded as a fundamental basis for criteria selection. Public comments are useful information when making decisions to determine the criteria set, because for major disasters, especially those are closely related to the interests of public, public like a shareholder who has the right to determine performance indicators. But, Xu et al. (2019a, 2019b) did not consider the availability of public social media data. When a disaster event happens, the time element is crucial for the applicability of the model, public social data may not be available during the initial stage. Based on the idea of Xu et al using public social media data to extract decision criteria, we have considered the urgency of time, improved the decision process, and ensured the consistent applicability of decision method.

The two-stage optimization model proposed in this paper combines the advantages of LSGDM models with feedback mechanism and without feedback mechanism to meet the decision-making needs during a short-time period. Firstly, the model inspired by multiplayer game theories theoretically simulates the decision-making process of multiple rounds of consultation and discussion with feedback mechanism in real disaster management while it is a model without feedback mechanism, making sure group conflict is within a certain range and effectively saves decision-making time. Secondly, clustering was made before the optimization model. Clustering controls the number of players within a moderate scale to ensure the decision-making quality. Finally, the proposed method can fully consider the opinions of every decision maker including public, which makes the decision result a high degree of satisfaction.

The rest of this paper is arranged as follows: Sect. 2 presents some related preliminaries for the proposed method. Section 3 indicates the main problems to be solved. In Sect. 4, we propose a two-stage optimization model for LSGDM in disaster management. In Sect. 5, a case study illustrates the method's application. Finally, conclusions are drawn in Sect. 6.

2 Preliminaries

In the following, we introduce some basic concepts and models related to our research.

2.1 The 2-Tuple Fuzzy Linguistic Representation Model

Decision-making under disastrous situations is accompanied by uncertain information and dynamic situations, most decision makers tend to express their preferences with linguistic variables or fuzzy values instead of crisp numbers (Hao et al. 2018). Herrera and Martinez (2001) proposed a 2-tuple linguistic representation model that can unify the information assessed in linguistic hierarchies term sets without loss of information.

Definition 1 Let $S = \left\{s_0, s_1, \dots, s_g\right\}$ be a linguistic term set, $\beta \epsilon \left[0, g\right]$ be the result of an aggregation of the indices of a set of labels assessed in S, $\left(s_\gamma, \alpha\right)$ be linguistic 2-tuples, $s_\gamma \in S$ and $\alpha \in [-0.5, 0.5)$, s_γ represents the linguistic label of the information; α is a numerical value expressing the value of the translation from the original result β to the closest index label γ in S, i.e., the symbolic translation.

Follows are the functions to make transformations between linguistic 2-tuples and numerical values. Using Formula (1), we can translate a numerical number into a linguistic 2-tuple.

$$\Delta : \left[0, g\right] \rightarrow s \times [-0.5, 0.5)$$
$$\Delta(\beta) = \begin{cases} s_\gamma & \gamma = round(\beta) \\ \alpha = \beta - r & \alpha \in [-0.5, 0.5) \end{cases} \tag{1}$$

Using Formula (2), we can translate a linguistic term into a real number which is between 0 and g.

$$\begin{aligned} \Delta^{-1} &: s \times [-0.5, 0.5) \rightarrow [0, g] \\ \Delta^{-1}\left(s_\gamma, \alpha\right) &= \gamma + \alpha = \beta \end{aligned} \tag{2}$$

Furthermore, if we want to unify the dimensions, we can map the linguistic terms to [0, 1] by using Formula (3).

$$\begin{aligned} \Delta^{-1} &: s \times [-0.5, 0.5) \rightarrow [0, 1] \\ \Delta^{-1}\left(s_\gamma, \alpha\right) &= \frac{\gamma+\alpha}{g} \end{aligned} \tag{3}$$

2.2 TF-IDF

TF-IDF (Salton and Buckley 1988) is a classical term-weighting approach in automatic text retrieval and data mining. TF (term frequency) is used as part of the term-weighting system to measure the frequency of occurrence of the terms in documents or query texts. IDF (inverse document frequency) is a measure of the universal importance of a word, varies inversely with the number of documents to which a term is assigned in a collection of documents.

Definition 2 Let tf_{td} means the raw term frequency (number of times a term t occurs in a document d), N is total number of documents in collection, and df_t is number of documents to which a term is assigned. A classical term weight is defined as follow:

$$\omega_{td} = tf_{td} \times log\left(\frac{N}{df_t}\right) \tag{4}$$

3 Problem Description

Suppose M experts from the emergency disaster decision-making large-scale group $E = \{e_1, e_2, \dots, e_M\}$, in which the e_i is i th member. There are P emergency disaster response plans $X = \{x_1, x_2, \dots, x_P\}$ in which x_l is l th plan. After a disaster event happens, the decision group need to quickly choose the best response plan to guide and support for response actions. At the same time, public are very concerned about the event, they express their thoughts about the event on social media.

To simplify the problem, we suppose that individuals give their preferences informatively (Austen-Smith and Banks 1996): all of their public or private information is revealed through their preference values, and no conflict of interests among decision makers. The plan with the highest aggregated preference value given by the group E is the best choice.

4 A Two-Stage Optimization Model for LSGDM in Disaster Management

4.1 Outline of the Proposed Model

The members of LSGDM for disaster management are composed of two types. One type is the public, they are like shareholders, they care about the event, and the outcome is related to their interests, but lack of expertise or experience in disaster rescue and disposal. Thus, if they participate in the decision, they are suitable for determining the decision-making criteria and weights. The other type is experts, they have related expertise and experience, can give the evaluation values under each criterion to every alternative.

For calculating the criteria and weights, this paper proposes the idea that using TF-IDF approach to extract criteria and their weights from comments on social media. If the public comment data can be obtained in real time before decision-making is started, then we can use the real-time crawling data. Otherwise, we should search data of similar past events to support the decision.

For aggregate the preferences of experts, this paper proposes a two-stage optimization method inspired by multiplayer game theories. Due to the complexity of LSGDM for disaster management, experts come from different professional fields, have different values, different experiences. It's better to seriously consider everyone' evaluations or opinions, meaning the aggregated result should be as satisfactory to each expert as possible. At the same time, the decision is time pressure, the shorter the decision time, the better. However, the decision group is large-scale, existing heterogeneous preferences and conflicts. In order to reach the group consensus, the conflicts should be controlled in a range. The discussing and bargaining process is essential but time-consuming. Multiplayer game faces the similar situation but can directly calculate the solution, and it saves time. So, inspired by multiplayer game theories, this paper proposes a two-stage optimization model to aggregate preferences of large-scale group. The proposed method saves time, improves decision efficiency while ensuring the satisfaction of decision makers. First, k-means clustering algorithm is used to analyze the preference structure of large-scale group. After clustering, the large-scale group is divided into several clusters, each cluster represents a different opinion and can be regarded as a player in next steps. Secondly, the negotiation process of different conflicting opinions is like a process of multiplayer negotiation games, and solution of the two-stage optimization model is the satisfactory result that being accepted by group. Finally, the preference values of large-scale group are aggregated, and the reliability of the decision result is analyzed.

The main steps of the method are shown in Fig. 1.

4.2 The Calculation of Criteria and Their Weights

Decision criteria and their weights are obtained from public comment data. One reason we consider this idea is that disastrous events often have a wide range of impacts and are closely related to the public interest. The public likes a shareholder who has

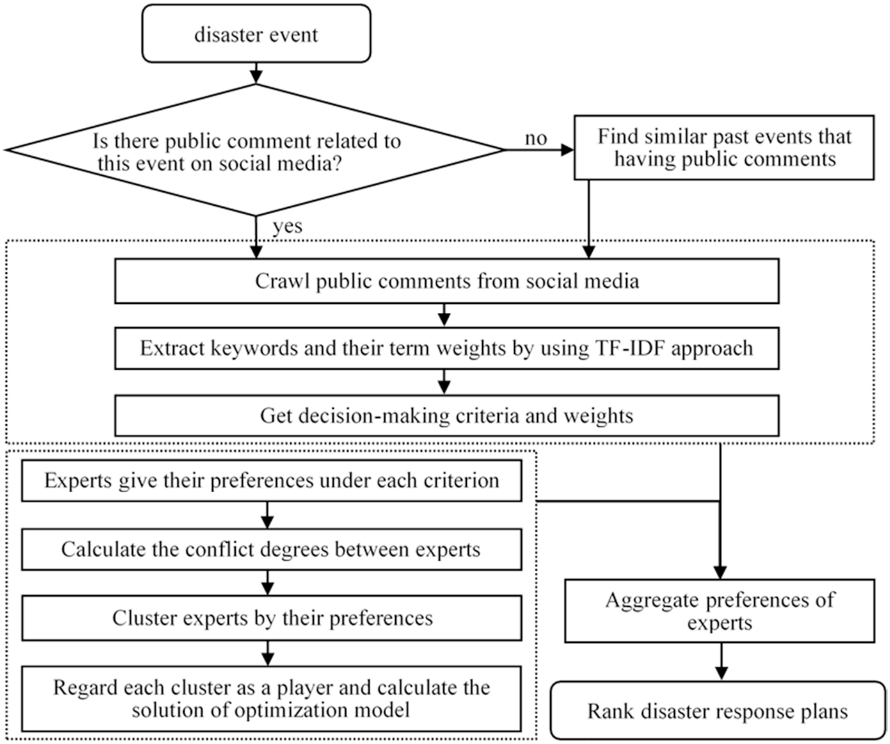

Fig. 1 Outline of the propose method for LSGDM in disaster management

the right to determine performance indicators that are indicated by decision criteria and weights. The other reason is that getting more useful information can enhance the objectivity of decision-making.

For a specific disaster decision, we crawl related public comments from social media. Then, we use TF-IDF approach to extract keywords and their weights from the comments. To simplify the process, we choose the TOP 100 (or more, that depends on the situation) keywords and cluster them into $N(j = 1, 2, \ldots, N)$ topics, each topic represents a criterion. The sum of keywords' weight in a topic is the weight of criterion. After normalizing the weights of topics, we get the weight of criteria $W = \left(w_j\right)_{1\times N}$.

4.3 Clustering Experts by Their Preferences

As we mentioned in Sect. 1, more decision makers do not always mean better decision results. Although, more decision makers can make up for the lack of knowledge and experience of individuals or small groups, as well as increase public satisfaction with the decision-making results. But, the larger groups exhibiting more "social loafing" that people working in groups tend to expend less effort than people working as individuals, which in conversely may induce decision makers to lessen the effort they take, giving an offset effect on decision quality improvement (Karau and Williams 1993). On the issue of optimal group size, Thomas and Fink (1963) think that a moderate group size of 5 to 7 people is the most effective and can get a more correct opinion. Cummings et al. (1974) think that if the focus is on the quality of decision-making, it is more suitable for a group of 5 to 11 people.

For LSGDM, the number of decision makers is more than 20. To ensure the quality of decision-making, it is better to use clustering methods to make sure the players' number in a moderate level. Even after clustering, not much preference information is lost because the number of experts in large-scale group is so large that while there are different preferences, there are also similar opinions. Clustering brings similar preferences together to form a cluster, which greatly reduces the complexity of subsequent calculations, and controls the number of players at a moderate level to ensure the quality of decisions.

To simplify the aggregation, k-means clustering algorithm (MacQueen 1967) is used to cluster experts by their preference information. One can control the number of players by choosing the value of the parameter K to control the quality of the decision. We recommend K to be between 5 and 11.

For clustering, we need to give the definition of conflict degree between two experts. Suppose the preference of expert e_i is recorded as $A^i = \left(a^i_{lj}\right)_{P\times N}$ after the conversion of Formula (3).

Definition 3 According to the weighted Hamming distance, the preference conflict degree between expert e_{i_1} and expert e_{i_2} is defined as follow:

$$\mathrm{D}\left(e_{i_1}, e_{i_2}\right) = \sum_{j=1}^{N} \left|a^{i_1}_{lj} - a^{i_2}_{lj}\right| w_j \tag{5}$$

As we known, the greater the difference in preferences between experts, the greater the value. Since after the conversion of Formula (3), $a^{i_1}_{lj}, a^{i_2}_{lj} \in [0, 1]$ and after normalized, $\sum w_j = 1$, then, $D\left(e_{i_1}, e_{i_2}\right) \in [0, 1]$.

After clustering, the experts those owing similarity preferences are in a cluster. The large-scale group is divided into K clusters. Let the number of experts in the cluster C^k be $n_k (k = 1, 2 \dots, K)$, then $\sum_{k=1}^{K} n_k = M$. Each cluster represents a class of preferences, each cluster is a player in a multiplayer game. The preference of the player (cluster) C^k is defined as follows:

Definition 4 The average preference values of all experts within C^k is defined as the preference of player C^k:

$$CA^k = \left(ca^k_{lj}\right)_{P\times N} = \left(\frac{\sum_{i=1, e_i \in C^k}^{n_k} a^i_{lj}}{n_k}\right)_{P\times N} \tag{6}$$

Then, based on the preference of player, we define the satisfaction function of player C^k to plan l.

Definition 5 The satisfaction function of player C^k to plan l is defined as follows:

$$U_l^k\left(t_1, t_2, \dots t_N\right) = 1 - \sum_{j=1}^{N} \left(t_j - ca_{lj}^k\right)^2 w_j \tag{7}$$

Where $t_j \in [0, 1](j = 1, 2, \dots, N)$ is the independent variable of the function U_l^k, represents the preference value under j th criterion; the range of U_l^k is [0, 1]. The greater the difference between the preference of final decision-making result and player C^k, the smaller the satisfaction of C^k.

4.4 The First Stage Optimization Mode of Maximizing Satisfaction of Players

The basic idea of the proposed model is to obtain a relatively satisfactory decision result within a proper conflict level among decision makers within a short time. To ensure the satisfactory level, every kind of reference should be respected whether it is a minority opinion or an uncooperative opinion (Xu et al. 2015c). That is the main purpose of the first stage.

In order to absorb preference of every player in the game, we propose an optimization model with the maximum personal satisfaction of players as the objective function, and each player's satisfaction is equal as constraints.

$$\begin{array}{ll} & \max \quad U_l^k \\ s.t. & \begin{cases} U_l^1 = U_l^2 = \dots = U_l^K \\ 0 \le t_j \le 1, j = 1, 2 \dots, N \end{cases} \end{array} \tag{8}$$

The solution of Formula (8) makes the satisfaction of each player in the game equal, and the individual satisfaction is maximized under the premise of equal satisfaction.

Formula (8) depicts an ideal state. Sometimes the model may have no optimal solution. Thus, we propose an approximated model as follows: try to make the satisfaction of every player equal.

$$\begin{array}{c} min \quad \sum_{k_1=1}^{K} \sum_{k_2=1}^{K} \left(U_l^{k_1} - U_l^{k_2}\right)^2 \\ s.t. 0 \le t_j \le 1, j = 1, 2, \dots, N. \end{array} \tag{9}$$

4.5 The Second Stage Optimization Mode of Minimizing Conflict Between Players

In real-life disaster management decision-making, it is impossible for the player to consider only his or her own preference, otherwise it will easily lead to the prisoner's dilemma. Therefore, in the process of LSGDM, the consideration of the whole large-scale group should take precedence over the consideration of personal player in the game. Based on this idea, an optimization model is established with the objective of minimizing the conflict of large-scale group and constraints that the satisfaction of each player should not be lower than the satisfaction of the first stage.

Definition 6 To depict the conflict of large-scale group of experts, the conflict function of large-scale group is defined as:

$$Conf_l\left(t_1, t_2, \dots, t_N\right) = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}\left(t_j - a_{lj}^i\right)^2 \omega_j}{M} \tag{10}$$

Since $0 \le t_j \le 1$, $0 \le a_{lj}^i \le 1$, $\sum_{j=1}^{N} w_j = 1$ then $Conf_l \in [0, 1]$.The larger the conflict, the greater the value $Conf_l$.

The second stage optimization model is as follow:

$$\begin{aligned} & min \quad Conf_l \\ s.t. & \begin{cases} U_l^1 \ge U_l^1(T1^*) \\ U_l^2 \ge U_l^2(T1^*) \\ \cdots \\ U_l^K \ge U_l^K(T1^*) \\ 0 \le t_j \le 1, j = 1, 2, \dots, N \end{cases} \end{aligned} \tag{11}$$

Where $T1^*$ is the solution for the first stage optimization model. Let the solution of the second stage optimization model be T^*.

4.6 Aggregate Preferences of Large-Scale Group

To rank the disaster response plans, we need to aggregate the preference value TA_l for plan l by using Formula (12):

$$TA_l = T^* \cdot W^T \tag{12}$$

where T^* is the aggregated preference of large-scale group.

4.7 Steps of the Two-Stage Optimization Model for LSGDM in Disaster Management

Step 1 Determine if there are any comments related to the event on social media. If the answer is yes, crawl data related to the subject of the event before experts making decisions. If not, search relevant comment data of similar events for reference.
Step 2 Crawling public comments from social media, using TF-IDF approach to extract keywords and weights from public comments, then we get the set of criteria $N(j = 1, 2, \dots, N)$ and the weight of criteria $W = \left(w_j\right)_{1\times N}$.
Step 3 Collect experts' preferences from decision support system which are expressed by 2-Tuple Fuzzy Linguistic value. Using Formula (3) translate them into real numbers between 0 and 1. The preference of expert e_i is recorded as $A^i = \left(a_{lj}^i\right)_{P\times N}$. Steps 4-6 are used to aggregate the preference of experts for a disaster response plan l.

Step 4 Using Formula (5) to calculate the conflict degrees between two experts, then using K-means clustering algorithm to cluster experts into K clusters. Using Formula (6) to calculate the preferences of all clusters $C^k(k = 1, 2, \dots, K)$.
Step 5 Regard each cluster as a player in a multiplayer game. Using Formula (7)–(11) to calculate the equilibrium solution T^*, T^* is the aggregate preference of all experts.
Step 6 Using Formula (12) to calculate the preference value TA_l for plan X_l.
Step 7 Repeat steps 4-6 under the evaluation for all plans and we get all preference values $\mathrm{TA}_l(l = 1, 2, \dots, P)$.
Step 8 Compare values of all $\mathrm{TA}_l(l = 1, 2, \dots, P)$ and choose the plan with the largest value.

4.8 Reliability Analysis of Decision Result

In general, it would be good to compare the properties of the decision method. Guttman (1998) defined an optimal decision rule, and it maximizes the sum of the group members' benefits, subject to the constraint that it be stable. A stable decision rule produces a well-defined preference ordering, given the preference orderings of the members of the decision-making. In our paper, the solution of two-stage optimization model is the preference value of large-scale group which can give a preference ordering according to the value of solutions. Each player (cluster) represents a kind of opinion, satisfaction degree reflects the benefit of player, it's better to have a greater total or average satisfactory degree. Additionally, to respect every opinion, the final decision result needs to maintain the balance of each kind of opinion as much as possible, so the deviation of satisfaction among players is as small as possible. As a result, it is suitable to compare the mean and standard deviation of players' satisfactory degree to judge the reliability of decision result.

By substituting the equilibrium solution T^* into the satisfaction function of Formula (7) , we can get each cluster's satisfactory degree: $U_l^1\left(T^*\right)$, $U_l^2\left(T^*\right), \dots, U_l^K\left(T^*\right)$. Then, we calculate their mean $\bar{U}$ and standard deviation U_σ of satisfactory degrees respectively. According to the value of $\bar{U}$ and U_σ, there is a basic judgment on the results of LSGDM. The larger $\bar{U}$ is, the higher satisfaction is, the better decision-making result is; the smaller U_σ is, the smaller divergence of opinions of large-scale group is. Table 1 shows the details.

5 Case Application

5.1 Case Background

On August 10, 2019, Super Typhoon Lekima landed in Zhejiang Province, China at a strong typhoon level. The maximum wind power of the landing center was 52m/s (super typhoon), which severely damaged coastal areas of eastern China. This is an natural disaster event, if not handled properly, it may cause greater losses. Thus, Xiamen disaster management center had gathered 20 experts in meteorology, typhoon,

Table 1 Mean and standard deviation of players' satisfaction

$\bar{U}$	U_σ	Judgments of preference aggregation	Suggestions
Big	Small	Very good. The satisfactory degree of decision result is high, the opinions are acceptable by majority players	Accept the result
Big	Big	Good. The satisfactory degree of decision result is high, but opinions differ greatly. The cluster that have the maximal $U_l^k(T^*)$ dominates the final result	Accept the result depends on the situation
Small	Big	Poor. The satisfactory degree is low and the divergence is great	Expound the viewpoints of all players and make decision again after in-depth discussion
Small	Small	Very poor. The satisfactory degree is low. The result of decision-making is not satisfactory	Collecting more decision-making information and introducing experts with new knowledge structure into the decision-making group, then make decisions again

flooding, electricity, disaster relief and other fields. There existed three plans: plan X_1 focuses on evacuation of personnel, plan X_2 focuses on the guarantee of disaster relief materials, plan X_3 focuses on the prevention of secondary disasters. The large-scale group of experts needed to quickly select a typhoon response plan to deal with the incident. To determine the criteria set of decision, the management center searched the history database and found out that Typhoon Meranti on September 15, 2016 are similar event, which landed in Xiamen City with the same 52m/s maximum wind force at the center.

5.2 Decision Making Process

Step 1 Before the typhoon is coming, there are seldomly people taking about the event on social media, the real time data are not enough to support the decision criteria set. As a result, the disaster management center decided to use historical data of similar intensity typhoon Meranti as a reference for decision criteria extraction.

Step 2 Using "台风莫兰蒂, (Typhoon Meranti)" as the hashtag to crawl related public comments from Sina Weibo and Tencent Weibo , we get 19,498 comments, which ranges from September 15, 2016 to December 14, 2016, covering the emergency and post-disaster disposal related comments of typhoon Meranti. Using "*jieba.analyse.extract_tags*" function in Jieba liabrary in Python to extract keywords and weights from public comments. This paper selects the top 300 keywords and clusters them into seven categories, just as shown in Table 2. Ignore keywords of stop words, event description, emotional expressions, we get four decision criteria: Timeliness, Economic loss, Disaster relief, Casualties. The weights of TF-IDF corresponding to keywords are summed up and normalized as the weights of the criteria, as shown in Table 3.

Step 3 Collect experts' preference from decision support system which are in the form of linguistic values. The linguistic term set is S={s_0 = *extremely poor* , s_1 = *poor* , s_2 = *lightly poor* , s_3 = *general* , s_4 = *slightly good* , s_5 = *good* ,s_6 = *extremely good*}. The preferences given by experts are shown in Table 4 (Due to the large volume of the data, Table 4 only lists the experts' preferences for plan X_1). Using Formula (3) translate preferences in Table 4 into real num-

Table 2 Top 300 keywords

Categories	Number of keywords	Sum of ω_{td}
Stop words	117	1.2619
Event Description	85	1.7252
Emotional Expressions	30	0.2493
Timeliness	25	0.2299
Economic loss	23	0.2623
Disaster relief	17	0.1165
Casualties	3	0.0189

Table 3 The weights of criteria

Criteria N	Corresponding keywords	Weights W
Economic loss C_1	淹没 (submerge), 停电 (power cut), 冲毁 (destroyed), 三座 (three), 停水 (water failure), 扩散 (diffusion), 影响 (impact), 树 (trees), 来袭 (attack), 严重 (serious), 万户 (10,000 families), 受灾 (Disaster situation), 重创 (heavy damage), 满目苍夷 (desolation), 冲垮 (collapse), 强势 (strong), 受损 (damage), 停课 (suspend classes), 肆虐 (wreak havoc), 灾情 (suffering condition), 袭 (attack), 吹风 (wind), 遭受 (suffer)	0.42
Timeliness C_2	中秋 (Mid-Autumn Festival), 中秋节 (Mid-Autumn Festival), 过后 (later), 今天 (today), 作业 (busywork), 紧急 (emergency), 明天 (tomorrow), 今年 (this year), 凌晨 (wee hours), 消息 (news), 2016, 现在 (at present), 今早 (this morning), 一天 (one day), 目前 (now), 一日 (one day), 十年 (ten years), 假期 (vacation), 时候 (time), 时间 (time), 开始 (start), 这次 (this time), 小时 (hour), 晚上 (evening), 快点 (hurry up)	0.37
Disaster relief C_3	防抗 (prevent), 重建 (rebuild), 灾后 (post-disaster), 安全 (safe), 日后 (in the future), 预警 (early warning), 重修 (reestablish), 电网 (power grid), 防汛 (flood prevention), 电力设施 (power facilities), 重点 (key points), 抢修工作 (urgent repairs), 巡校 (patrol), 恢复 (restoration), 抢修 (emergency repair), 国家电网 (national power grid), 防范 (prevention)	0.18
Casualties C_4	小孩 (Children), 老人 (the old), 失踪 (missing person)	0.03

Table 4 The preferences of 20 experts for plan X_1

Expert	C_1	C_2	C_3	C_4	Expert	C_1	C_2	C_3	C_4
1	$(S_5,0.5)$	$(S_6,-0.4)$	$(S_1,0.3)$	$(S_6,-0.5)$	11	$(S_0,0)$	$(S_0,0.1)$	$(S_3,-0.1)$	$(S_3,0.4)$
2	$(S_4,0.2)$	$(S_2,-0.5)$	$(S_4,0.3)$	$(S_0,0)$	12	$(S_0,0.4)$	$(S_4,-0.3)$	$(S_0,0)$	$(S_5,0.1)$
3	$(S_4,0.3)$	$(S_4,0.2)$	$(S_0,0)$	$(S_2,-0.2)$	13	$(S_5,-0.4)$	$(S_1,-0.4)$	$(S_3,0.3)$	$(S_4,-0.4)$
4	$(S_5,0.4)$	$(S_2,0.3)$	$(S_4,-0.4)$	$(S_5,0.3)$	14	$(S_6,-0.4)$	$(S_3,-0.1)$	$(S_0,0.2)$	$(S_2,0.5)$
5	$(S_3,0.2)$	$(S_2,-0.4)$	$(S_2,-0.3)$	$(S_4,0.5)$	15	$(S_2,-0.1)$	$(S_2,0.2)$	$(S_0,0.2)$	$(S_2,-0.4)$
6	$(S_0,0.3)$	$(S_5,-0.4)$	$(S_0,0)$	$(S_5,0.1)$	16	$(S_0,0.3)$	$(S_4,-0.4)$	$(S_3,-0.1)$	$(S_5,-0.2)$
7	$(S_2,-0.2)$	$(S_0,0.4)$	$(S_2,-0.3)$	$(S_6,-0.4)$	17	$(S_5,-0.1)$	$(S_2,-0.3)$	$(S_6,-0.1)$	$(S_1,0.2)$
8	$(S_4,0)$	$(S_2,-0.3)$	$(S_0,0.1)$	$(S_5,-0.4)$	18	$(S_0,0.3)$	$(S_4,-0.2)$	$(S_5,-0.1)$	$(S_2,0.4)$
9	$(S_3,-0.1)$	$(S_2,0.1)$	$(S_5,-0.3)$	$(S_2,-0.3)$	19	$(S_4,-0.2)$	$(S_4,-0.5)$	$(S_4,0.4)$	$(S_1,-0.1)$
10	$(S_1,-0.2)$	$(S_3,-0.2)$	$(S_3,-0.3)$	$(S_6,-0.2)$	20	$(S_2,-0.3)$	$(S_0,0.3)$	$(S_3,-0.4)$	$(S_4,0)$

bers. The preference values are recorded in Table 5. The following steps 4-6 are the evaluation of response plan X_1.

Step 4 Using Formula (5) to calculate the conflict degrees between two experts; let $K = 5$, then using k-means clustering algorithm to cluster experts into 5 clusters;

Table 5 The preference values of 20 experts for plan X_1

Expert	C_1	C_2	C_3	C_4	Expert	C_1	C_2	C_3	C_4
1	0.9167	0.9333	0.2167	0.9167	11	0.0000	0.0167	0.4833	0.5667
2	0.7000	0.25	0.7167	0.0000	12	0.0667	0.6167	0.0000	0.8500
3	0.7167	0.7000	0.0000	0.3000	13	0.7667	0.1000	0.5500	0.6000
4	0.9000	0.3833	0.6000	0.8833	14	0.9333	0.4833	0.0333	0.4167
5	0.5333	0.2667	0.2833	0.7500	15	0.3167	0.3667	0.0333	0.2667
6	0.0500	0.7667	0.0000	0.8500	16	0.0500	0.6000	0.4833	0.8000
7	0.3000	0.0667	0.2833	0.9333	17	0.8167	0.2833	0.9833	0.2000
8	0.6667	0.2833	0.0167	0.7667	18	0.0500	0.6333	0.8167	0.4000
9	0.4833	0.3500	0.7833	0.2833	19	0.6333	0.5833	0.7333	0.15000
10	0.1333	0.4667	0.4500	0.9667	20	0.2833	0.0500	0.4333	0.6667

using Formula (6) to calculate the preferences of all clusters $C^k(k = 1, 2, \dots, K)$. The clustering results are shown in Table 6.

Step 5 Regard each cluster as a player. Using Formula (7)–(11) to calculate the solution $T1^* = (0.2124, 0.0000, 0.8782, 0.0003)$ and $T^* = (0.5225, 0.5525, 0.4925, 0.6200)$.

Step 6 Using Formula (12) to calculate the preference value TA_1 for plan X_1 and $\mathrm{TA}_1 = 0.5311$.

Step 7 Repeat steps 4–6 under the evaluation for all plans and we get all preference values $\mathrm{TA}_2 = 0.4674$, $\mathrm{TA}_3 = 0.4873$.

Step 8 Compare values of all TA_l, since $\mathrm{TA}_1 > \mathrm{TA}_3 > \mathrm{TA}_2$, plan X_1 is the best choice.

5.3 Reliability Analysis of Decision Result

Taking the evaluation of plan 1 as an example. The solution

$$T^* = (0.5225, 0.5525, 0.4925, 0.6200)$$

we substitute T^* into the satisfaction function [Formula (7)], calculate each cluster's satisfactory degree and the result is as follows: $U_1^1\left(T^*\right) = 0.9277$,

Table 6 The clustering result

Clusters	Number of experts	Members	Preferences of clusters
CL_1	1	e_{15}	(0.3167, 0.3667, 0.0333, 0.2667)
CL_2	16	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_{19}, e_{20}	(0.5052, 0.3948, 0.3490, 0.6187)
CL_3	1	e_{16}	(0.0500, 0.6000, 0.4833, 0.8000)
CL_4	1	e_{17}	(0.8167, 0.2833, 0.9833, 0.2000)
CL_5	1	e_{18}	(0.0500, 0.6333, 0.8167, 0.4000)

$U_1^2(T^*) = 0.9870$, $U_1^3(T^*) = 0.9044$, $U_1^4(T^*) = 0.8882$, $U_1^5(T^*) = 0.8834$. Then, the mean $\bar{U}$ and standard deviation U_σ of satisfactory degrees are calculated respectively, $\bar{U} = 0.9181$, $U_\sigma = 0.0422$. As we can see, cluster CL_2 who owns the largest number of experts has the highest satisfaction degree. The value of $\bar{U}$ is big and the value of U_σ is small, we can accept the decision result.

5.4 Comparison Analysis of Decision Result

To illustrate the effectiveness and superiority of the proposed method, we compared it with LSGDM methods with and without feedback mechanism, respectively.

5.4.1 Compare with a LSGDM Method that has Feedback Mechanism

Xu et al. (2015c) proposed a LSGDM method that considered non-cooperative behaviors and minority opinions, and it is a method with a feedback mechanism. Minority opinion subgroups were identified, and several rounds of thorough discussions and compromises were needed to make sure the consensus reaching a certain level. Applying the same original preference data of Xu's paper, we calculated using Xu's method and our method for LSGDM, respectively. Detail results can be seen in Table 7.

The length of decision time is composed of the time of giving original preferences, the time of discussion and the time of calculation. Both methods need time to give original preferences, and the time of calculation is much lower than time of discussion which can be ignored when calculating the time difference between two methods. So, time differences between two methods are reflected by the time of discussion. The result of Xu's method in Table 7 is the decision result after 3 rounds of negotiation and adjustment. Suppose each round of discussion and manual adjustment consumes 5 minutes, then our methods save at least 15 minutes to reach a group consensus. At the same time, the satisfaction of our decision-making result

Table 7 Comparison result with Xu's method

Categories	Xu's method	Our method
Iterations	3	–
The ranking result	$x_5 > x_4 > x_2 > x_1 > x_3$	$x_1 > x_2 > x_5 > x_4 > x_3$
The aggregated preference matrix	$\begin{bmatrix} 0.4561 & 0.5226 & 0.5055 \\ 0.5045 & 0.6544 & 0.5541 \\ 0.4895 & 0.4229 & 0.5148 \\ 0.6465 & 0.6444 & 0.5364 \\ 0.7088 & 0.7393 & 0.5023 \end{bmatrix}$	$\begin{bmatrix} 0.8525 & 0.4833 & 0.5251 \\ 0.6006 & 0.4801 & 0.9741 \\ 0.3896 & 0.5661 & 0.4450 \\ 0.5112 & 0.5209 & 0.4830 \\ 1.0000 & 0.000 & 0.000 \end{bmatrix}$
$\bar{U}$ and U_σ of alternative 1	$\bar{U} = 0.8247, U_\sigma = 0.1313$	$\bar{U} = 0.8807, U_\sigma = 0.0286$
$\bar{U}$ and U_σ of alternative 2	$\bar{U} = 0.8757, U_\sigma = 0.0673$	$\bar{U} = 0.9157, U_\sigma = 0.0108$
$\bar{U}$ and U_σ of alternative 3	$\bar{U} = 0.8954, U_\sigma = 0.0728$	$\bar{U} = 0.9292, U_\sigma = 0.0402$
$\bar{U}$ and U_σ of alternative 4	$\bar{U} = 0.8942, U_\sigma = 0.1434$	$\bar{U} = 0.9081, U_\sigma = 0.0876$
$\bar{U}$ and U_σ of alternative 5	$\bar{U} = 0.8318, U_\sigma = 0.1260$	$\bar{U} = 0.8643, U_\sigma = 0.0640$

was not affected, values of $\bar{U}$ are higher, and values of U_σ are lower than those of Xu's under all alternatives.

5.4.2 Compare with a LSGDM Method that has No Feedback Mechanism

Xu et al. (2018) proposed a two-stage method to reach group consensus for LSGDM problems, where iterative algorithm was built to process conflicts within sub-clusters and large-scale group. The preferences were modified using pre-defined formulas and rules until the conflict of group is below a pre-defined threshold. It is a method that has no feedback mechanism since no discussion and manual modification were committed before changing preferences. Applying the same original preference data of Xu's paper, we use Xu's method and our method to make decisions, respectively. The results are shown in Table 8, and we can see the satisfaction of our method was higher comparing with Xu's method, since values of $\bar{U}$ are higher and values of U_σ are lower than those of Xu's under all alternatives.

5.4.3 Compare with a LSGDM Method that Considering Public Opinion

Xu et al. (2019b) proposed a novel LSGDM method based on data mining of public attribute preferences. Latent semantic analysis was applied to build an attribute-keyword lexicon, and fuzzy association rule mining was applied to extract attributes information of public opinion. This method is quite useful when considering public preferences in a big data era. But when applying it to emergency decisions that considering decision time, the emergency decision was making while the public data was forming at the same time, and it may not be able to quickly obtain public data in a limited time. So, we improved the decision process while applying TF-IDF approach to extract attribute information to make sure the attribute information was available when making an emergency decision. A historical public data of similar emergency events could be applied to the early stage of decisions, and the public data could also be conserved to apply it to the next similar situation's decision.

Table 8 Comparison result with Xu's method

Categories	Xu's method	Our method
The ranking result	$x_2 > x_1 > x_3 > x_4$	$x_4 > x_3 > x_2 > x_1$
The aggregated preference matrix	$\begin{bmatrix} 0.326 & 0.553 & 0.433 \\ 0.878 & 0.510 & 0.528 \\ 0.425 & 0.208 & 0.465 \\ 0.302 & 0.597 & 0.134 \end{bmatrix}$	$\begin{bmatrix} 0.476 & 0.454 & 0.370 \\ 0.393 & 0.447 & 0.627 \\ 0.558 & 0.454 & 0.650 \\ 0.427 & 0.599 & 0.523 \end{bmatrix}$
$\bar{U}$ and U_σ of alternative 1	$\bar{U} = 0.8362, U_\sigma = 0.0673$	$\bar{U} = 0.8593, U_\sigma = 0.0311$
$\bar{U}$ and U_σ of alternative 2	$\bar{U} = 0.8393, U_\sigma = 0.0984$	$\bar{U} = 0.8480, U_\sigma = 0.0396$
$\bar{U}$ and U_σ of alternative 3	$\bar{U} = 0.8481, U_\sigma = 0.1142$	$\bar{U} = 0.8661, U_\sigma = 0.0397$
$\bar{U}$ and U_σ of alternative 4	$\bar{U} = 0.8159, U_\sigma = 0.1103$	$\bar{U} = 0.8631, U_\sigma = 0.0327$

6 Conclusions

Considering the characteristic of time pressure in LSGDM for disaster management, inspired by multiplayer game theory, this paper proposes the maximization of the player's satisfaction and the minimization of the large-scale group's conflict two-stage optimization model for LSGDM in disaster management. It combines the advantages of LSGDM method with and without feedback mechanism. The idea of regarding clusters as players, building two-stage optimal negotiation model, and directly calculating the final negotiating solution has the advantage of a feedback mechanism model and saves discuss and negotiation time. Compare with Xu's method (2018) that has no feedback mechanism, satisfaction of our methods was higher. Compared with Xu's (2015c) method that has feedback mechanism, our methods save at least 15 minutes to reach a consensus while the satisfaction of decision result was not affected. Also, the proposed method improves the decision process of introducing public social media data to improve the objectivity and feasibility of the method.

Introducing public social media data into LSGDM has many advantages such as containing more amount of decision information, improving satisfaction of decision-making result and so on. However, how to efficiently use this kind of information is a problem worth long-term research. This paper provides a possible method. When the public decision makers were included, their role is like a shareholder, and expert group is like the professional agent. Experts reflect their professional opinions through preference values, and public embody their interests by determining criteria and weights. That is the relationship we considered in this paper between traditional expert group and public decision makers.

In big data era, collecting public data such as social media data and calculating mass data is feasible. For further study of LSGDM problems, on the one hand, starting with public data, how to extract useful decision-making information from it, how to effectively integrate it with decision-making information of traditional expert large-scale group are directions that can be further improved; On the other hand, in terms of large-scale group information aggregation, combining machine learning algorithms with traditional LSGDM methods to achieve large-scale group self-learning and intelligent optimization can greatly improve decision efficiency and quality.

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