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An improved consensus-based group decision making model with heterogeneous information

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ABSTRACT

In group decision making (GDM) problems, it is natural for decision makers (DMs) to provide different preferences and evaluations owing to varying domain knowledge and cultural values. When the number of DMs is large, a higher degree of heterogeneity is expected, and it is difficult to translate heterogeneous information into one unified preference without loss of context. In this aspect, the current GDM models face two main challenges, i.e., handling the complexity pertaining to the unification of heterogeneous information from a large number of DMs, and providing optimal solutions based on unification methods. This paper presents a new consensus-based GDM model to manage heterogeneous information. In the new GDM model, an aggregation of individual priority (AIP)-based aggregation mechanism, which is able to employ flexible methods for deriving each DM's individual priority and to avoid information loss caused by unifying heterogeneous information, is utilized to aggregate the individual preferences. To reach a consensus more efficiently, different revision schemes are employed to reward/penalize the cooperative/non-cooperative DMs, respectively. The temporary collective opinion used to guide the revision process is derived by aggregating only those non-conflicting opinions at each round of revision. In order to measure the consensus in a robust manner, a position-based dissimilarity measure is developed. Compared with the existing GDM models, the proposed GDM model is more effective and flexible in processing heterogeneous information. It can be used to handle different types of information with different degrees of granularity. Six types of information are exemplified in this paper, i.e., ordinal, interval, fuzzy number, linguistic, intuitionistic fuzzy set, and real number. The results indicate that the position-based consensus measure is able to overcome possible distortions of the results in large-scale GDM problems.

1. Introduction

Making a decision by a group is a widespread process in our daily life. The need of multiple views makes group decision making (GDM) increasingly necessary in numerous societies and organizations today. In a GDM scenario, each decision maker (DM) can express his/her preferences with different information granularities and different structures, depending on their various background, knowledge, and experience. Therefore, GDM models need to deal with heterogeneous information to meet the demands stemming from modern societal and technological contexts. Chiclana et al. [1] first presented a notable GDM model to integrate three different preference representations, i.e., preference orderings, utility functions, and fuzzy preference relations. They employed transformation functions to unify the available information into fuzzy preference. The ordered weighted averaging (OWA) operator is then employed to aggregate the individual fuzzy preferences into a collective decision. Since then, a variety of GDM models have been proposed based on the idea of unification of heterogeneous information. Examples include Herrera-Viedma et al. [2] transforming heterogeneous information into fuzzy preferences; Herrera et al. [3], Herrera et al. [4], Mata et al. [5], Martínez et al. [6] unifying heterogeneous information into fuzzy sets pertaining to the pre-determined basic linguistic term set (BLTS); Herrera et al. [7] and Cabrerizo et al. [8] presenting a fuzzy linguistic methodology with the aid of the transformation functions between labels from different levels. A good review on multi-granular linguistic models is presented in Morente-Molinera et al. [9], in which the advantages and drawbacks of various multi-granular linguistic methods are studied in detail. In these models, the process of handling heterogeneous information consists of three steps: (1) unification process, where the heterogeneous preferences are transformed into one unified form, e.g. fuzzy set in BLTS; (2) aggregation process, where appropriate aggregation operators are employed to aggregate the unified individual preferences into a collective preference; and (3)

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selection process, where the best alternative(s) are selected or the final ranking order is obtained based on some criteria. These GDM models are called unification-based GDM models according to the way of handling heterogeneous information.

While unification-based GDM models provide a valuable framework for solving GDM problems with heterogeneous information, they suffer from some shortcomings that need further improvements. One difficulty is the increasing complexity of unifying the heterogeneous information when a large number of DMs is involved. A typical example is the intricacy of determining appropriate membership functions for the linguistic term when the heterogeneous information is transformed into the linguistic term sets (fuzzy sets) in BLTS. The other difficulty is that the unification-based GDM models probably fail to provide optimal solutions even though transformation functions with good properties are used to unify heterogeneous information. As an example, the collective decision violates the Pareto principle of social choice theory when the heterogeneous information was transformed into fuzzy preference (see Example 1). In order to overcome these drawbacks, an AIP-based aggregation mechanism, which is able to avoid violating the Pareto principle, is utilized to aggregate the individual preferences in this paper. Owing to its flexibility in deriving each DM's individual priority, the AIP-based aggregation mechanism alleviates the computational complexity and information loss issues caused by unifying heterogeneous information.

Another contribution of the proposed GDM model is that it employs different revision schemes to reward or penalize DMs. In large-scale GDM problems, the disagreement among DMs is inevitable since different DMs have different opinions. Therefore, the revision process needs to be considered in order to achieve a final solution with a high level of consensus. However, owing to the existence of a large number of DMs in large scale GDM problems, some DMs can decide not to accept the advices and refuse to modify their original preferences. To deal with such non-cooperative DMs, a weight penalization scheme is utilized to reduce the importance of those non-cooperative DMs. Such a weight penalization scheme is essentially equivalent to performing a compulsory revision for the non-cooperative DMs. Therefore, it is able to make use of the information provided by the non-cooperative DMs. Additionally, based on the idea of Axelrod [10], the non-cooperative DMs would gradually become cooperative if they are being sanctioned by others. As a result, the weight penalization scheme is capable of facilitating the consensus-reaching process. For the cooperative DMs, the advice generation mechanism proposed by Pérez et al. [11] is incorporated into our proposed model to control the amount of advices required by each DM and generate the advice in function of the DM's importance degree. In addition, an improved iterative revision process is performed for the cooperative DMs.

Most existing revision processes are usually guided by the current consensus degree and/or consistency degree [12,13]. However, we notice that it is possible for the aggregated temporary collective opinion to represent the group opinion differently owing to the existence of the conflicting opinions. Therefore, the consensus degree, which is usually calculated based on the similarity between the temporary collective opinion and individual opinions, can be prejudiced by the conflicting opinions. In order to overcome the prejudice, the temporary collective opinion is first derived by aggregating only those non-conflicting ones. Then the opinion closest to the current temporary collective preference would be retrieved from the pair of conflicting opinions. Therefore, the temporary collective group decision is more appropriate to reflect the opinions of most DMs. As a result, it is more accurate to be used for guiding the subsequent revision process.

Finally, in order to measure the consensus degree more appropriately, a position-based similarity measure related to the ranking orders of alternatives is defined to calculate DMs' consensus degree. The proposed position-based similarity measure is effective in keeping more general information since it has a lower granularity level in information processing. Therefore, it is more robust and is able to overcome the possible distortion of results brought by identical rankings of alternatives that have different preference priority vectors associated with them (see Examples 2 and 3).

This paper is organized as follows. Section 2 presents the background and preliminary knowledge pertaining to this research. The possibility that the existing unification-based GDM models produce violation of the Pareto principle is illustrated by some examples. In order to tackle this problem, a general scheme of the GDM model to handle heterogeneous information is provided in Section 3, where the AIP method is utilized to aggregate the priorities, while preserving the Pareto principle. In Section 4, different priority generating methods are reviewed to derive the priorities from individual preferences with heterogeneous information. Section 5 defines a position-based consensus measure, which is robust and efficient for evaluating the degree of agreement among DMs. In addition, a definition of conflicting DMs is provided to assist the consensus reaching process in the proposed GDM model. Section 6 provides a detailed revision procedure to reward or penalize the preferences provided by cooperative or non-cooperative DMs. Finally, concluding remarks and suggestions for future studies are presented in Section 7.

2. Background

In this section, the violation of the Pareto principle caused by the transformation function of the existing unification-based GDM models is examined. Two aggregation mechanisms, i.e., AIP and AIJ (aggregation of individual judgment), are investigated. As a result, AIP is chosen as the aggregation method owing to its advantages for handling large-scale GDM problems with heterogeneous information. Finally, an algorithm for handling conflicting opinions in large-scale GDM models is introduced.

2.1. Violation of the Pareto principle

An example pertaining to violation of the Pareto principle by unifying heterogeneous information into fuzzy preference is illustrated, as follows.

Example 1. Let $X=\{x_1, x_2, x_3, x_4, x_5\}$ be five alternatives. Three DMs, i.e., MP_1, MP_2, and MP_3, provide their preferences by using heterogeneous preferences. DM_1 provides ordinal information on the evaluation of X, denoted by MP_1: $x_1 > x_2 > x_4 > x_3 > x_5$, DM_2 and DM_3 present multiplicative-based preference relations, MP_2, and fuzzy preference relations, MP_3, respectively.

$$MP_2 = \begin{pmatrix} 1 & 1 & 4 & 5 & 5 & 5 \\ 1 & 1 & 4 & 7 & 3 & 4 \\ 1/4 & 1/4 & 1 & 2 & 2 & 2 \\ 1/5 & 1/7 & 1/2 & 1 & 2 & 3 \\ 1/5 & 1/3 & 1/2 & 1/2 & 1 & 2 \\ 1/5 & 1/4 & 1/2 & 1/2 & 1/2 & 1 \end{pmatrix},$$

$$MP_3 = \begin{pmatrix} 0.50 & 0.53 & 0.56 & 0.56 & 0.60 & 0.60 \\ 0.47 & 0.50 & 0.80 & 0.60 & 0.80 & 0.90 \\ 0.44 & 0.20 & 0.50 & 0.60 & 0.70 & 0.55 \\ 0.44 & 0.40 & 0.40 & 0.50 & 0.60 & 0.60 \\ 0.40 & 0.20 & 0.30 & 0.40 & 0.50 & 0.55 \\ 0.40 & 0.10 & 0.45 & 0.40 & 0.45 & 0.50 \end{pmatrix}$$

(i) Unifying heterogeneous information into fuzzy preference relations

Based on the general idea of unification-based GDM models, preferences MP_1, MP_2, and MP_3 are usually unified into fuzzy preference relations, denoted as P_1, P_2, and P_3. In this example, MP_3 remains unchanged, i.e., $P_3 = MP_3$ since it has been expressed by a fuzzy preference relation The ordinal preference provided by DM_1 is unified as fuzzy preference relations by using the transformation function provided by Chiclana et al. [1], i.e., $p_{ij}^k = \frac{1}{2}\left[1 + \frac{o^k(x_j)-o^k(x_i)}{n-1}\right]$, which has been proven to preserve consistency of original information [14]. Therefore, the obtained fuzzy preference relation is as follows:

$$P_1 = \begin{pmatrix} 0.5 & 0.6 & 0.8 & 0.7 & 0.9 & 1 \\ 0.4 & 0.5 & 0.7 & 0.6 & 0.8 & 0.9 \\ 0.2 & 0.3 & 0.5 & 0.4 & 0.6 & 0.7 \\ 0.3 & 0.4 & 0.6 & 0.5 & 0.7 & 0.8 \\ 0.1 & 0.2 & 0.4 & 0.3 & 0.5 & 0.6 \\ 0 & 0.1 & 0.3 & 0.2 & 0.4 & 0.5 \end{pmatrix}$$