Knowledge-Based Systems 70 (2014) 189–202

Contents lists available at ScienceDirect

Knowledge-Based Systems

journal homepage: www.elsevier.com/locate/knosys

A two-stage dynamic group decision making method for processing ordinal information

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ARTICLE INFO

Article history:
Received 19 October 2013
Received in revised form 24 June 2014
Accepted 25 June 2014
Available online 4 July 2014

Keywords:
Power Average operator
Support function
Dominance-based rough set approach
Ordinal preference
Group decision making

ABSTRACT

In group decision making (GDM) problems, ordinal data provide a convenient way of articulating preferences from decision makers (DMs). A number of GDM models have been proposed to aggregate such kind of preferences in the literature. However, most of the GDM models that handle ordinal preferences suffer from two drawbacks: (1) it is difficult for the GDM models to manage conflicting opinions, especially with a large number of DMs; and (2) the relationships between the preferences provided by the DMs are neglected, and all DMs are assumed to be of equal importance, therefore causing the aggregated collective preference not an ideal representative of the group's decision. In order to overcome these problems, a two-stage dynamic group decision making method for aggregating ordinal preferences is proposed in this paper. The method consists of two main processes: (i) a data cleansing process, which aims to reduce the influence of conflicting opinions pertaining to the collective decision prior to the aggregation process; as such an effective solution for undertaking large-scale GDM problems is formulated; and (ii) a support degree oriented consensus-reaching process, where the collective preference is aggregated by using the Power Average (PA) operator; as such, the relationships of the arguments being aggregated are taken into consideration (i.e., allowing the values being aggregated to support each other). A new support function for the PA operator to deal with ordinal information is defined based on the dominance-based rough set approach. The proposed GDM model is compared with the models presented by Herrera-Viedma et al. An application related to controlling the degradation of the hydrographic basin of a river in Brazil is evaluated. The results demonstrate the usefulness of the proposed method in handling GDM problems with ordinal information.

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1. Introduction

Ordinal information is commonly used to rank the criteria or alternatives in group decision making (GDM) problems [22,48,50,53]. As an example, when a customer is asked to compare different flavors of cakes, it is natural for him/her to give an ordinal preference. Unlike the numerical-based measure, ordinal information is unable to specify the degree of importance of the criteria or alternatives exactly. It only provides the order information pertaining to the criteria or alternatives. This leads to a number of difficulties in aggregating ordinal information presented by a group of Decision Makers (DMs). In this aspect, a lot of aggregation methods based on ordinal evaluation of individual rankings have been proposed in the literature for achieving a collective group preference. Essentially, the aggregation models for tackling GDM problems with ordinal information can be divided into four categories:

(1) majority-based models [6,16,35], which produce the collective preference by using the majority-based approach, e.g. the simple majority rule, the Borda method, the majorities based on differences of votes, and their variants;
(2) ranking weight-based models [1,2,25], which aggregate individual ordinal preferences by converting ordinal ranking into numerical-valued weight information;
(3) distance-based models [17,26], which generate the collective preference by minimizing the total aggregated disagreement between each individual and the final ranking;

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http://dx.doi.org/10.1016/j.knosys.2014.06.025
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(4) other methods, e.g. [50,53] employed the non-numeric aggregation operators based on the max/min operator.

A good review is provided by Cook [15]. Despite the extensive research on GDM problems with ordinal information, there are some weaknesses associated with the available methods. One of them is the necessity of managing conflicting opinions in a large group. In large-scale decision making problems, conflicting opinions are inevitable owing to differences among the preferences provided by the DMs. Such conflicting opinions cannot result in a final consensus. Sometimes, conflicting opinions can lead to disagreement after lengthy discussion [30], because some DMs do not want to alter their initial opinions. A number of studies have been conducted to deal with possible conflicts by discarding the preferences of DMs who do not contribute towards achieving a consensus [36], or penalizing them by reducing their influences on the final collective group decision [51].

In order to overcome the aforementioned shortcoming, a data cleansing process, which aims to eliminate conflicting preferences among the DMs prior to the aggregation process, is employed in this paper. The proposed data cleansing process is motivated by the idea of *soft consensus*, which can be achieved *when most of the participating DMs agree on the most important alternatives*. Soft consensus was firstly proposed by Kacprzyk [27]. Due to its ability to guide the consensus process in a flexible way until an agreement (not necessarily a full agreement) is achieved among the DMs, soft consensus-based methods have been widely used in various GDM problems with satisfactory results [7,24,28]. The basic idea of soft consensus-based methods is that it allows a group to obtain a limited agreement among the DMs, which provides the foundation for integrating the data cleansing process into the GDM model. In other word, the limited agreement among the DMs can still be achieved by eliminating conflicting opinions from the DMs which do not contribute towards achieving a consensus.

Another challenge is that most aggregation operators in the existing GDM models that handle ordinal preferences usually neglect the relationship (agreement or disagreement) among the DMs. A variety of aggregation operators, which include the weighted average operator, ordered weighted average (OWA) operator [49], numerical weighting linguistic average operator [43], induced ordered weighted averaging operators [9], type-1 OWA operators [14,29,56,57] and interval valued operators [54], have been developed. However, all these aggregation operators are unable to validate the association between two or more DMs. This is because their aggregation is based on prior information gathered beforehand, without measuring the degree of support among the DMs before reaching a final consensus. To overcome this problem, the Power Average (PA) operator introduced by Yager [52] is employed in this paper. With the aid of the PA operator, we are able to allow the values being aggregated to support and reinforce each other; therefore taking the relationships among the arguments into consideration in the aggregation process. One notable property of the PA operator is that it captures both the features of mode-like methods to find the most typical value, and the averaging-type operator to aggregate the data. The PA operator has since been widely used in many multi-criteria decision making and evaluation problems [33,44]. Recently, Zhou and Chen [55] extended the PA operator to a linguistic environment by combining it with the generalized mean operator, and applied to a multi-attribute GDM problem. Xu and Cai [46] defined an uncertain power weighted average operator and an uncertain power ordered weighted average operator, and proposed a method for GDM using interval fuzzy preference relations.

However, most aggregation algorithms based on the PA operators treat decision making as a static event, namely, the collective opinions aggregated by using the PA operator are directly regarded as the group's final decision. This is impractical because a simplistic aggregation process would render the final decision invalid when conflicting opinions that differ widely are forced to conform to a full consensus. As a result, there is a need to embed a revision mechanism in the aggregation process, which allows the group to reach a satisfactory decision. Therefore, we propose an algorithm with an iterative mechanism to assist the DMs to revise their opinions in order to reach a high degree of group consensus in this paper. A number of GDM models with revision (feedback) mechanisms have been proposed in the literature. Some examples are the models proposed by Herrera-Viedma et al. [21,22,32]. These models focus on identification of the preferences that need to be revised, and then provide the corresponding directions of changes. In order to indicate the change rules clearly, other models with advice generation have been proposed by Alonso et al. [3], Meta et al. [12], Wu and Chiclana [39,40]. These models not only provide the DMs with the identification of preference values to be changed, but also with the advice to revise the preference values in the light of additional information too. All these GDM models with feedback mechanisms offer a valuable means to help the DMs in achieving a high degree of consensus. These feedback mechanisms embrace the same purpose, i.e., to generate advice to help the group to achieve a higher degree of consensus among the DMs. The feedback mechanisms also share a similar consensus control strategy, i.e., when the overall degree of consensus is lower than a predetermined threshold, the revision process starts until the overall degree of consensus reaches the threshold. However, the advice generation procedure is different, for example, the ones proposed by Herrera-Viedema et al. [22,21] only suggested the direction of changes, while those proposed by Sergio Alonso et al. [3], Chiclana et al. [12], and Wu and Chiclana [39,40] provided both direction and value of changes to the DMs. However, it is found that they included the influence of the conflicting opinions when they provide the guidance for the revision process. In our proposed feedback mechanism, both direction and value of changes to the DMs are also provided, but the revision is guided by the collective opinions aggregated from the non-conflicting ones only; therefore avoiding bias caused by the conflicting opinions. Additionally, our mechanism is more flexible owing to the predetermined aggregation threshold. Our iterative mechanism assumes that opinions with a satisfying support degree have the power to influence the group's decision; therefore those DMs' opinions can be aggregated to contribute to the final group decision. Our algorithm for aggregating the opinions from different DMs consists of two stages. In the first stage, the data cleansing process eliminates the opinions that cause conflicts based on the support degree of each DM. The second stage comprises an iterative process, which allows the DMs to revise their opinions in order to obtain an acceptable support degree, and then arrive at the final group decision by using the PA operator.

Methodologically, defining a proper support function of the PA operator is the core of the aggregation process. The commonly used form is defined by Yager [52], which is based on parameterized formulations. However, parameterized formulations restrict the wide usage of the PA operator since these parameters have to be determined by the DMs, or some metaheuristic techniques. Motivated by the dominance-based rough set approach (DRSA) presented by Greco et al. [19], we propose a new non-parameterized definition of the support function, which is appropriate for coping with ordinal preferences provided by the DMs. It is also easy to understand since it has an explicit explanation.

The rest of the paper is organized as follows. Section 2 reviews the concept of the PA operator and the representation of ordinal preferences, along with an introduction to the general scheme of consensus-based GDM models. Section 3 defines a support function to measure the support degree of the DMs using DRSA.

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