



A partial binary tree DEA-DA cyclic classification model for decision makers in complex multi-attribute large-group interval-valued intuitionistic fuzzy decision-making problems



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ABSTRACT

This paper proposes the idea of combining “interest groups” with the practical decision information to classify the decision makers (DMs) in complex multi-attribute large-group decision-making (CMALGDM) problems in interval-valued intuitionistic fuzzy (IVIF) environment. It constructs a partial binary tree DEA-DA cyclic classification model to achieve the multiple groups’ classification of DMs. Not only does this method provide references for the classification of DMs when the decision information is known, but it also lays foundations for DMs’ effective weight determination and the aggregation of decision information. First, this paper normalizes all of the cost attributes into benefit attributes to avoid the wrong decision result. Second, it employs the C-OWA operator to transform IVIF number (IVIFN) samples into single-valued samples. With respect to this transformation, this paper provides the corresponding BUM functions of DMs according to their risk attitudes; therefore, the preference information of DMs can be more objectively aggregated. Third, this paper adopts the partial binary tree DEA-DA cyclic classification model to present an accurate classification of DMs. Thus, for each interest group, group members with different interest preferences can be distinguished and distributed to the appropriate groups. Finally, to show the feasibility and validity of the model, we give an illustrative example.

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1. Introduction

Group decision-making problems have gradually become a focus of academia. Indeed, numerous group decision-making methods have emerged [1–7] since the ranking model of group alternatives was proposed by the French mathematician Borda in 1781. However, because of the constant development of society and the economy, decision environments, decision groups and decision attributes of some major societal and economic problems are undergoing profound changes. Not only do these decision problems have many aspects that must be considered and that require the regulation of multiple relations and interests, but they also usually lack convincing theories that one may refer to, due to the complexities of decision problems. Chen [8] classified these problems into complex multi-attribute large-group decision-making (CMALGDM) problems and summarized the following four features of such problems: (a) decision makers (DMs) of a decision-making group can make decisions at relatively different times and in relatively different places in network environment; (b) DMs’ number is usually more than 20, and this number is not limited to personnel

inside the organization, as it includes different personnel outside the organization. Moreover, there exist both competitions and connections caused by interests among DMs; (c) there may exist certain connections among decision attributes; (d) the preference information of the DMs is uncertain.

The aim of a CMALGDM problem is to obtain an alternative order or an alternative selection that is based on the decision information. However, due to the complexity of this type of problem, current research into CMALGDM problems is mainly focused on classification or clustering of DMs, consistency of groups, determination of attributes’ weights, determination of DMs’ weights, and aggregation of decision information [8]. These research efforts can be regarded as the intermediate steps to design a decision process, and they have laid the foundation for solving the CMALGDM problem. After acknowledging the previous research, we devote ourselves to the classification of DMs and give a novel classification model for DMs in the CMALGDM problem in interval-valued intuitionistic fuzzy (IVIF) environment.

We first explain why we discuss the CMALGDM problem in the IVIF environment (i.e., why the preferences of the DMs are given by IVIF numbers (IVIFNs)) but not in fuzzy environment. Indeed fuzzy set theory has been widely applied to each aspect of modern society since it was initiated by Zadeh [9]. However, the traditional

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fuzzy set faces certain limitations, as it fails to present an overall description of all of the information that is relevant to the studied problems. Thus, Atanassov [10] proposed the intuitionistic fuzzy set (IFS), and this set simultaneously considers information that pertains to membership degree (MD) and non-membership degree (ND). Atanassov and Gargov [11] furthered IFS by introducing the IVIF set (IVIFS), which represents MD and ND by two closed subintervals of the interval $[0, 1]$. This method has effectively expanded the IFS's capability to handle uncertain information, and furthermore, it has solved practical decision-making problems more effectively. In fact, in CMALGDM problems, DMs are not always certain about their given decision or preference information and they often have some degree of uncertainty. Therefore, the IVIFN is a suitable option to address these situations.

There is an important reason for us to propose a new classification model. In fact, many classification models (or algorithms) in the IVIF environment have been established recently. Xu et al. [12] gave a clustering algorithm for IVIFSs that is based on association and equivalent association matrices. Xu [13] proposed a hierarchical algorithm for clustering IVIFSs based on traditional hierarchical clustering approach. Indeed, using the fuzzy C-means clustering approach as well as the distance measures, Xu and Wu [14] developed an IVIF C-means algorithm to cluster IVIFSs. Furthermore, Zhao et al. [15] investigated the clustering model for IVIFSs based on the graph theory. The main feature of these algorithms (except for the fuzzy C-means-based algorithm) is as follows: the classification result relies greatly on the choice of the threshold. For example, with respect to decision-making problems with n DMs, these DMs might be classified into any type from one type to n types in the practical classification process, which depends on the threshold. However, it is usually very hard to provide the exact number or range of the appropriate threshold in the real world. On the contrary, it is always easy to divide DMs into some "interest groups" when one has prior knowledge. For example, we can a priori classify the DMs into several groups by their statuses, careers, or income levels. Therefore, when the threshold is difficult to obtain, it is beneficial to combine interest groups with practical decision information to solve classification or clustering problems instead of determining the threshold.

It may be argued that we should use the interest groups as our classification result and that it is therefore unnecessary to reclassify the interest groups according to the decision information. We give an example to refute this notion. In the decision-making process of consumption, it is true that there exist remarkable differences in groups that have different income levels. However, even people who have the same income level may have different decision attitudes. Thus, it is more scientific to classify groups of different income levels in advance and then differentiate the members of these income-based groups from each other; afterwards, the procedure is to select individuals with different attitudes in each interest group and classify them into more reasonable groups.

However, it is not obvious how we can realize this goal. It is well known that DEA-DA is a discriminant analysis approach which can judge the group belonging for new observations [16]. The Japanese scholar Sueyoshi has conducted research on this model and proposed various improved models [17–19], where the MIP (mixed integer programming) DEA-DA is the most mature model. Hence, for a two-group case, we intend to adopt the MIP DEA-DA model to adjust the initial classification result (i.e., the interest groups). The reason why we could adopt this model to solve our problem will be provided in Section 2.3. However, due to the potential computational error of any computer or software, this goal cannot necessarily be achieved by conducting a MIP DEA-DA analysis only once. Therefore, we will conduct periodic MIP DEA-DA analyzes of the two groups until the two-group samples remain unchanged. Indeed, although the MIP DEA-DA model is capable of handling

overlapping and misjudged phenomena, it cannot handle the classification of multiple groups. Sueyoshi [19] extended the MIP DEA-DA model to equip it with the ability to classify multiple groups. However, this method can only handle the dataset that can be arranged according to a particular sequence [19]. In this regard, this paper introduces the idea of a partial binary tree to transform an h -type classification problem into $h - 1$ binary classification problems. In summation, we define the improved MIP DEA-DA model as the partial binary tree DEA-DA cyclic classification model.

As the proposed model can only handle single-valued information, the key to solving the problem is to find an effective technique to transform IVIFN samples into single-valued samples, and it is essential to reduce the possible loss of information. To realize this goal, we adopt the C-OWA operator [20], which was proposed by Yager, to transform IVIFN samples into single-valued samples. Because the corresponding basic unit-interval monotonic (BUM) function of DMs' risk attitudes are given during the transformation, the decision information of DMs can be more objectively aggregated. After this aggregation, we employ the partial binary tree DEA-DA cyclic classification model to offer an accurate classification of DMs.

The remainder of the paper is organized as follows: We provide basic concepts of IFSs and IVIFSs, and briefly introduce the C-OWA operator and the MIP DEA-DA model in Section 2. Section 3 succinctly describes the DMs classification issue in CMALGDM problems and proposes the C-OWA operator-based method to transform IVIFN samples into single-valued samples. Section 4 introduces the partial binary tree DEA-DA cyclic classification model in detail, and an illustrative example is proposed to investigate the feasibility of this classification method in Section 5. In addition, a comparison with one of the state-of-the-art classification methods is contained in this section. Section 6 concludes the paper and provides suggestions for future research.

2. Preliminaries

In this section, we first give the basic concepts of IFSs and IVIFSs (this material is found in Section 2.1). Then, a brief introduction of the C-OWA operator is given in Section 2.2. Finally, the MIP DEA-DA model is introduced in Section 2.3, and the reason why we can use this model is also given in this section.

2.1. Basic concepts of IFSs and IVIFSs

Atanassov [10] generalized the fuzzy set and defined the concept of the IFS which is listed in Definition 1.

Definition 1 10. Suppose X is a non-empty set. Then, we call

$$A = \{ \langle x, \mu_A(x), \nu_A(x) \rangle | x \in X \} \quad (1)$$

the IFS. Here $\mu_A(x)$ denotes the MD of x to A ; $\nu_A(x)$ denotes the ND of x to A . Moreover, we have $\mu_A(x) \in [0, 1]$, $\nu_A(x) \in [0, 1]$, and $0 \leq \mu_A(x) + \nu_A(x) \leq 1$ for every $x \in X$.

To simplify expressions, Xu and Yager [21] defined $\alpha = (\mu_\alpha, \nu_\alpha)$ as the intuitionistic fuzzy number (IFN) and used it to represent the element in IFS.

However, because of the complexity of objective things, it is sometimes difficult to express MD and ND in an IFS with accurate real numbers; instead, interval numbers are often more suitable. In this regard, Atanassov and Gargov [11] furthered the IFS and proposed the IVIFS, which is found in Definition 2.

Definition 2 11. Suppose X is a non-empty set. Then, we define

$$\tilde{A} = \{ \langle x, \tilde{\mu}_A(x), \tilde{\nu}_A(x) \rangle | x \in X \} \quad (2)$$

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