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Aggregating decision information into Atanassov's intuitionistic fuzzy numbers for heterogeneous multi-attribute group decision making

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ABSTRACT

The aim of this paper is to propose a new aggregation method to solve heterogeneous MAGDM problem which involves real numbers, interval numbers, triangular fuzzy numbers (TFNs), trapezoidal fuzzy numbers (TrFNs), linguistic values and Atanassov's intuitionistic fuzzy numbers (AIFNs). Firstly, motivated by the relative closeness of technique for order preference by similarity to ideal solution (TOPSIS), we propose a new general method for aggregating crisp values, TFNs, TrFNs and linguistic values into AIFNs. Thus all the group decision matrices for each alternative which involves heterogeneous information are transformed into an Atanassov's intuitionistic fuzzy decision matrix which only contains AIFNs. To determine the attribute weights, a multiple objective Atanassov's intuitionistic fuzzy programming model is constructed and solved by converting it into a linear program. Subsequently, comparison analyses demonstrate that the proposed aggregated technology can overcome the drawbacks of existing methods. An example about cloud computing service evaluation is given to verify the practicality and effectiveness of the proposed method.

1. Introduction

In cloud-based IT management, cloud computing service (CCS) evaluation problems have been extensively studied [1,2]. Since the real-life CCS provider selection problems often involve multiple attributes and actions such as costs, scope and performance, IT security, reliability, management capacity and flexibility, they may be ascribed to a kind of multi-attribute decision making (MADM) problems [3]. The increasing complexity of realistic social environment makes it difficult for a single decision maker (DM) or expert to consider factors of various aspects. Therefore, group decision making (GDM) has been the subject of intense research in decision science area [4]. In general, GDM with multiple conflicting attributes (criteria) are simply called the multi-attribute group decision making (MAGDM) problems [4]. However, in most practical MAGDM problems, since the inherent uncertainty and vagueness of the objects, the attribute values given by DMs are not always represented in the form of crisp values [1–4], and some are better suitable to be expressed in fuzzy values [5–13]. The two main representation types of fuzzy values are [5]: numeric case [6–8] and linguistic case [5,9–13]. Numeric cases which are used to measure quantitative attribute [14], may be interval numbers, Atanassov's intuitionistic fuzzy numbers (AIFNs) [6], triangular fuzzy numbers (TFNs) [7] and trapezoidal fuzzy numbers (TrFNs) [8]. Linguistic cases which are used to measure qualitative attribute, may be fuzzy set linguistic representation and 2-Tuple linguistic representation [10]. In spite of being less precise than numerical values, linguistic values make expert judgment more reliable and informative and are more appropriate for representing approximate values that are too complex to be represented using precise numerical values [11].

In general, the assessments may be measured in various types of attribute values (such as real numbers, fuzzy numbers and linguistic values) are called heterogeneous MAGDM problems by Chiclana et al. [15]. The heterogeneous MAGDM problem has been successfully applied to the fields of GDM [16,17], outsourcing [18], sustainable project selection [19], human resources performance evaluation [20], supply chain coordination [21], etc. The key to settling such problems is how to aggregate all individual decisions with heterogeneous

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information into collective one with uniformed information [15]. Following the lines of Chiclana et al. [15], many subsequent useful and valuable methods have been proposed to study the aggregation process in heterogeneous MAGDM. Those methods can be roughly classified into two categories:

(1) The distances based methods [14,16,18,22–28]. Li et al. [14] proposed a systematic approach to solving heterogeneous MAGDM. In this method, the weighted Minkowski distance is used to measure differences between the alternative and both the negative and positive ideal solution, and the relative closeness degree of alternative is used to ranking the alternatives. Based on the reference distance, Ma et al. [22] developed a fuzzy multi-criteria group decision making (MCGDM) decision support system, which can deal with different types of information including boolean values, linguistic terms and real numbers. Wan and Li [23] and Li and Wan [24,25] extended the Linear Programming Technique for Multidimensional Analysis of Preference (LINMAP) and presented fuzzy linear programming methods to solve heterogeneous multi-attribute decision making (MADM) problems. Wan and Li [26] defined the IFS-type consistency and inconsistency indices based on the Euclidean distances to the ideal solutions and proposed an Atanassov's intuitionistic fuzzy programming method for heterogeneous MAGDM with Atanassov's intuitionistic fuzzy truth degrees whose attribute values are described by real numbers, intervals, AIFNs and TrFNs. Further, Wan and Dong [27] put forward an interval-valued Atanassov's intuitionistic fuzzy mathematical programming method for hybrid MCGDM with interval-valued Atanassov's intuitionistic fuzzy truth degrees whose decision data are expressed in the forms of real numbers, intervals, AIFNs, TFNs and interval-valued Atanassov's intuitionistic fuzzy sets (IVAIFSs). Subsequently, Wan and Li [28] developed a new fuzzy mathematical programming method for solving heterogeneous MADM problems whose attribute values are presented by real numbers, interval numbers, linguistic values, TrFNs, IFSs, IVAIFSs. Zhang et al. [16] constructed a maximizing deviation model based on the distances to integrate the heterogeneous information, and then applied their method in strategic freight forwarder selection problem. The aforementioned distance based methods are seem to be effective to solve heterogeneous MAGDM. However, it should be pointed out that the final ranking indexes of all alternative obtained by these methods [14,16,18,22–28] are the distances to positive ideal solution or relative closeness. These ranking indexes are crisp values and cannot express the uncertainty and impreciseness of original decision information. Thus, information loss inevitably occurs in these methods.

(2) The transformation techniques based methods [15,17,29–33]. To avoid information loss, several different transformation techniques [15,17,29–33] have been proposed for converting the heterogeneous information into the homogeneous information. In existing researches, the heterogeneous information is often transformed into fuzzy preference relation [15], 2-tuple linguistic set [29,30] or linguistic term set [31–33]. Taking fuzzy preference relations as a based representation, Chiclana et al. [15] presented some fuzzy transformation functions for dealing with heterogeneous information (including preference orderings, utility values and fuzzy preference relations). Herrera et al. [29] developed a method to unify the heterogeneous information composed of real numbers, interval numbers and linguistic values into the 2-tuple linguistic information. Then, the collective assessment for each alternative can be obtained by 2-tuple linguistic weighted average operator. Further, considering the experts' social interactions and judgments, Pérez et al. [30] proposed three social network analysis 2-tuple linguistic based induced ordered weighted averaging (IOWA) operators. Chuu [31] proposed a fusion method for converting different linguistic scales (multi-granularity linguistic term sets) and numerical scales into a basic linguistic term set. Based on the type-1 ordered weighted averaging (TIOWA) operator [32], Mata et al. [33] developed a new TIOWA methodology to consensus reaching processes in multi-granularity linguistic contexts, which can directly handle linguistic values with different cardinality and semantic without the need to perform any transformation to unify the information. Recently, Chen et al. [17] reviewed the fusion process with heterogeneous preference structures in GDM.

As an extension of fuzzy sets, Atanassov's intuitionistic fuzzy (AIF) sets (AIFSs) [6] has better agility in expressing the uncertainty and ambiguity. However, the aforesaid literature survey reveals that there is no investigation on aggregating heterogeneous decision information into AIFNs [6] for the heterogeneous MAGDM problems. The signification for aggregating heterogeneous decision information into AIFNs can be explained by the following four facts: (1) AIFSs theory has attracted broad studies from different aspects [34]. Wu and Chiclana [35] proposed an attitudinal expected score function of AIFN, and used it to construct fuzzy preference relation (FPR) from a given intuitionistic FPR (IFPR). Furthermore, Wu and Chiclana [36] developed new attitudinal expected score and accuracy functions, and verified a set of properties. Wu and Chiclana [37] presented a consistency based procedure to estimate missing values in IFPRs. Ureña et al. [38] proved that the sets of reciprocal IFPRs and asymmetric FPRs are mathematically isomorphic. (2) AIFN has a wide application prospect. It has been extensively applied to various fields, such as clustering analysis [39], fingerprints authentication [40] and decision making [41–47], to name a few. (3) There are several transformation methods to defuzzify fuzzy number into a final crisp value, including the mean of maximum method and the center of area method [5,48]. However, these defuzzificaion methods present a limitation that a fuzzy number loses its fuzziness because the final crisp value ignores the shape of the resulting membership function [49]. (4) AIFN can deliver more useful information since it can describe the characteristics of affirmation, negation and hesitation simultaneously. For example, in an actual cloud computing service (CCS) [1,2] evaluation, the trustworthiness of a provider can be assessed by an AIFN (0.3, 0.4), which means that the trustworthy degree of CCS is 0.3, the untrustworthy degree is 0.4, and the indeterminacy is 0.3. However, it may be not easy to establish the crisp values for the membership and non-membership of AIFN because sufficient information is unavailable in real problems.

In this paper, a key issue that needs to be addressed for heterogeneous MAGDM is how to integrate a heterogeneous group decision matrix into an AIF decision matrix, which is very interesting yet relatively sophisticated to dispose. There are two major difficulties and challenges in the process of aggregating heterogeneous information: (1) How to establish the dissatisfactory bounds and satisfactory bounds by the attribute (column) vector. It is usually difficult to distinguish the dissatisfaction and satisfaction of different formats of attribute values. (2) How to derive reasonably the membership degree, non-membership degree and hesitancy degree of attribute vector. These parameters are basic component elements of an AIFN, but it is difficult to make them satisfies the definition of an AIFN. Currently, there are some studies focused on aggregating crisp values into AIFN. For instance, Yue [44] and Yue et al. [45] employed Golden Section idea to aggregate crisp values into AIFN. Yue et al. [46] proposed the method based on Minimax Criterion to aggregate crisp values into AIFN for MAGDM. More recently, Yue [47] developed a new useful and practical method for aggregating crisp values into AIFN, which is simpler in the sense of calculation. Although these aggregation methods [44–47] have some advantages, there are some limitations:

(1) The aggregation technique of Yue [47] may lead to some unreasonable results (see the cases discussed in Section 5.1 in detail).