Computers & Industrial Engineering 98 (2016) 185–194

Contents lists available at ScienceDirect

Computers & Industrial Engineering

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

An integrating OWA–TOPSIS framework in intuitionistic fuzzy settings for multiple attribute decision making

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ARTICLE INFO

Article history:
Received 24 November 2015
Received in revised form 22 April 2016
Accepted 16 May 2016
Available online 19 May 2016

Keywords:
Intuitionistic fuzzy numbers
Fuzzy TOPSIS
Information loss
Multiple attribute group decision making

ABSTRACT

In this paper, we develop an integrating OWA–TOPSIS approach in intuitionistic fuzzy environment to tackle fuzzy multiple attribute decision making problems. The proposed intuitionistic fuzzy OWA–TOPSIS method provides a general framework of diverse fuzzy information aggregation process including different determination methods of extreme points. There are six different types of information aggregation (*s–p–d* type, *p–s–d* type, *s–d–p* type, *p–d–s* type, *d–s–p* type and *d–p–s* type) following the different sequences of source aggregation, preference aggregation. During the different aggregation scenarios, positive ideal points and negative ideal points are identified as a point, a vector or a matrix. A real application example is provided to demonstrate in detail the proposed approach. The comparative results in total 32 experiments show the rankings consistency and different levels of information loss in the six different aggregation types. On the whole, the ranks are most precise in *d–s–p* and *d–p–s* types, and more precise in *s–p–d* and *p–s–d* types than that in *s–d–p* and *p–d–s* types.

1. Introduction

Multiple attribute decision making (MADM) is a practical tool for decision makers (DMs) to rank and evaluate different alternatives following the multiple performance indexes (criteria, factors, attributes). MADM can be viewed in a variety of practical situations in current economic society, such as new product pricing strategies evaluation (Baykasoğlu, Gölcük, & Akyol, 2015), performance evaluation of manufacturing plants (Yu & Hu, 2010), location analysis of distribution center of supply chain (He, Wang, & Zhou, 2009), comprehensive evaluation of product quality (Yang & Chou, 2005). MADM provides a systematic model framework to solve the complex decision problems based on the evaluation of multiple attributes. A number of methods have been developed to solve the MADM problems, such as MEW (multiplicative exponential weighting), SAW (simple additive weighting), AHP (analytic hierarchy process) and TOPSIS (technique for order performance by similarity to ideal solution). More approaches can be viewed in recent state-of-the-art reviews of MADM (Figueira, Greco, & Ehrgott, 2005; Liou & Tzeng, 2012; Turskis & Zavadskas, 2011; Zavadskas, Turskis, & Kildienė, 2014).

TOPSIS is a classical technique in dealing with MADM problems (Shih, Shyur, & Lee, 2007). It helps DMs carry out analysis and comparisons in ranking their preferences of the alternatives. The basic idea of the TOPSIS is straightforward and intuitive: calculate each alternative's shortest distance from positive ideal point (PIP) and farthest distance from the negative ideal point (NIP), and then aggregate the separate distance information to reach overall evaluation results (Hwang & Yoon, 1981). TOPSIS has been applied to solve selection/evaluation problem because it has a sound logic that represents the rationale of human choice. In order to handle the uncertain ratings and the weights of the criteria in an imprecise and uncertain environment, the TOPSIS method has been extended into group environment (Anisseh, Piri, Shahraki, & Agamohamadi, 2011; Yu, Guo, Guo, & Huang, 2011; Yuan & He, 2012; Zhang & Yu, 2012). And each DM can use fuzzy linguistic terms to give the assessments. For instance, Boran, Genç, Kurt, and Akay (2009) extended the TOPSIS method with intuitionistic fuzzy set to select appropriate supplier and applied IFWA (intuitionistic fuzzy weighted average) method to aggregate the intuitionistic fuzzy numbers. Ye (2010) proposed an extension of the TOPSIS method with interval-valued intuitionistic fuzzy numbers to solve the partner selection problem under incomplete and uncertain information environment. In this study, they identified PIPS and NIPS for each decision maker by obtaining the maximum and minimum values of membership non-membership components in interval-valued

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http://dx.doi.org/10.1016/j.cie.2016.05.029
0360-8352/

intuitionistic fuzzy numbers. Zhang and Yu (2012) also extended the TOPSIS with interval-valued intuitionistic fuzzy numbers, and proposed a cross-entropy based weights of attributes determination method.

However, as far as we know, most of works using TOPSIS technique to multiple attribute group decision making (MAGDM) exist aggregations in decision process. According to the viewpoint proposed by Shih (2008), these works about aggregation in group decision making can be classified as external and internal aggregations. Roghanian, Rahimi, and Ansari (2010) called the two aggregating approaches first aggregation and last aggregation in their paper and compared the difference of these two aggregation method. Yue (2013) claimed that the decision information may be lost in the external or internal aggregation of TOPSIS procedure. To overcome this drawback, he proposed a novel TOPSIS method which avoiding information aggregation in the decision making process. And a systematic methodology was presented in his paper by employing Euclidean distance straightforward to obtain the separation of each alternative from the PIPs and NIPs. However, the proposed method of this study did not compare with the external and internal aggregations. And other some integrated approaches have also been proposed to deal with the decision information aggregation. Chen et al. (2011) developed a hybrid approach integrating OWA aggregation into TOPSIS to tackle the MAGDM problems. And three different aggregation schemes were developed to integrate OWA into the TOPSIS procedure. However, the authors did not consider the information loss in these aggregation processes and the pros and cons of these different aggregation methods. Also, the method cannot be employed in the fuzzy environment to address the uncertain information. From the present research, there exists little investigation on information loss levels in the aggregation process. Therefore, the purpose of this article is to analyze the advantages and disadvantages of different aggregation approaches involved in the integrating OWA–TOPSIS procedure in intuitionistic fuzzy environment, especially on the robustness and information loss problems in the aggregation process.

The remainder of the paper is organized as follows. In the next section, we briefly introduce some basic concepts related to intuitionistic fuzzy sets (IFSs), intuitionistic fuzzy OWA (IFOWA) and intuitionistic fuzzy TOPSIS. Section 3 presents the method to integrate the IFOWA operation into TOPSIS approach in intuitionistic fuzzy environment to cope with the MAGDM problems. The proposed intuitionistic fuzzy OWA–TOPSIS method is illustrated with a numerical example in Section 4. And then the comparison analysis is done to confirm the ranking consistency and information loss differences in the different aggregation types in Section 5. Finally, some concluding remarks are furnished in Section 6.

2. Preliminaries

In the following, we shall briefly introduce some basic concepts related to IFS, IFOWA and intuitionistic fuzzy TOPSIS.

2.1. Intuitionistic fuzzy sets

In order to handle uncertain information in MAGDM problems, the criteria evaluation approach based on IFS is introduced briefly in this section. Intuitionistic fuzzy set introduced by Atanassov (1986) is an extension of the classical fuzzy set theory, which is a suitable way to deal with the vagueness and uncertainty. And IFS theory has been applied in different areas. For the sake of understanding in the following sections, the basic concept of IFS is reviewed as below.

Definition 1. Let a set $X = \{x_1, x_2, \ldots x_n\}$ be a finite universal set. An IFS A on X is an object with the form $A = \{(x, \mu_A(x), \nu_A(x)) | x \in X\}$.

Where the functions $\mu_A : X \to [0,1]$ and $\nu_A : X \to [0,1]$ assign the degree of membership and the degree of non-membership to the element, respectively. And they are constrained by $0 \leqslant \mu_A(x) + \nu_A(x) \leqslant 1$.

In addition, for each IFS A, $\pi_A(x) = 1 - \mu_A(x) - \nu_A(x)$ is called the degree of indeterminacy or hesitancy, depicted as in Fig.1. The larger $\pi_A(x)$ is, the more uncertainly we know about x, and otherwise, the more certain we are about x.

Definition 2. Let $A = \{(x, \mu_A(x), \nu_A(x)) | x \in X\}$ and $B = \{(x, \mu_B(x), \nu_B(x)) | x \in X\}$ be two IFSs and λ be a positive real number. The following relations and operations are valid (Atanassov, 1986).

$$A \oplus B = \{(x, \mu_A(x) + \mu_B(x) - \mu_A(x)\mu_B(x), \nu_A(x)\nu_B(x)) | x \in X\} \quad (1)$$

$$A \otimes B = \{(x, \mu_A(x)\mu_B(x), \nu_A(x) + \nu_B(x) - \nu_A(x)\nu_B(x)) | x \in X\} \quad (2)$$

$$\lambda A = \{(x, 1 - (1 - \mu_A(x))^{\lambda}, (\nu_A(x))^{\lambda}) | x \in X\} \quad (3)$$

In order to calculate the distance between two IFSs, according to Szmidt and Kacprzyk (2000), the normalized Euclidean distance can be expressed in Definition 3.

Definition 3. Let $A = \{(x, \mu_A(x), \nu_A(x)) | x \in X\}$ and $B = \{(x, \mu_B(x), \nu_B(x)) | x \in X\}$ be two IFSs in $X = \{x_1, x_2, \ldots x_n\}$, then the normalized Euclidean distance between A and B is as follow (Szmidt & Kacprzyk, 2000):

$$d(A,B) = \sqrt{\frac{1}{2n}\sum_{i=1}^{n}\left\{(\mu_A(x_i) - \mu_B(x_i))^2 + (\nu_A(x_i) - \nu_B(x_i))^2 + (\pi_A(x_i) - \pi_B(x_i))^2\right\}} \quad (4)$$

For convenience, Xu and Yager (2006) called $\alpha = (\mu_\alpha, \nu_\alpha)$ an intuitionistic fuzzy number (IFN), where $\mu_\alpha \in [0,1]$, $\nu_\alpha \in [0,1]$, $\mu_\alpha + \nu_\alpha \leqslant 1$ and $\pi_\alpha = 1 - \mu_\alpha - \nu_\alpha$. Each IFN has a physical interpretation, for example, if $\alpha = (0.7, 0.2)$, then $\mu_\alpha = 0.7$, $\nu_\alpha = 0.2$ and $\pi_\alpha = 0.1$, which can be interpreted as "the vote for resolution is 7 in favor, 2 against, and 1 abstentions".

For comparison of IFNs, Chen and Tan(1994) defined a score function while Hong and Choi (2000) defined an accuracy function.

Definition 4. Let $\alpha = (\mu_\alpha, \nu_\alpha)$ be an IFN, a score function s_α and accuracy function h_α of α can be defined, respectively, as follows:

$$s_\alpha = \mu_\alpha - \pi_\alpha \nu_\alpha, \quad s_\alpha \in [-1, 1] \quad (5)$$

$$h_\alpha = \mu_\alpha + \nu_\alpha, \quad h_\alpha \in [0, 1] \quad (6)$$

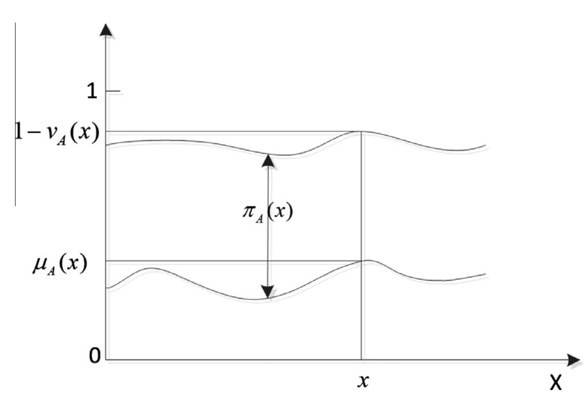

Fig. 1. An IFS.