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Supplier Evaluation in Green Supply Chain: An Adaptive Weight D-S Theory Model Based on Fuzzy-Rough-Sets-AHP Method

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Abstract

Supplier evaluation is of great significance in green supply chain management. Influenced by factors such as economic globalization, sustainable development, a holistic index framework is difficult to establish in green supply chain. Furthermore, the initial index values of candidate suppliers are often characterized by uncertainty and incompleteness and the index weight is variable. To solve these problems, an index framework is established after comprehensive consideration of the major factors. Then an adaptive weight D-S theory model is put forward, and a fuzzy-rough-sets-AHP method is proposed to solve the adaptive weight in the index framework. The case study and the comparison with TOPSIS show that the adaptive weight D-S theory model in this paper is feasible and effective.

Keywords

Adaptive Weight, D-S Theory, Fuzzy-Rough-Sets-AHP, Green Supply Chain, Supplier Evaluation

1. Introduction

With the fast growth of economic globalization, the resources and environment are facing enormous pressure now. Under this background, green supply chain management (GSCM) appears very important [1]. Green supply chain (GSC) was put forward in 1996 by the Manufacturing Research Center (MRC) of Michigan State University in a research on environmentally responsible manufacturing [2,3]. GSCM contains many contents, such as green supplier evaluation (GSE), green product design (GPD), green production (GP), green marketing and waste recycling (GMWR). As the upstream in the whole supply chain, the role of supplier in protecting the environment and saving costs can be transmitted to every part of the downstream through the supply chain, so as to improve the compatibility of supply chain and environment [4]. Manufacturing enterprises begin to measure the green degree of their suppliers, and one of the key steps to measure the green degree of an enterprise is how to choose the best supplier as a long-term partner [5]. By choosing the suitable green supplier, enterprises can largely improve the resource recycling rate and reduce pollutant emissions, and provide green control and processing for raw materials supplied by suppliers. Thus, the whole supply chain will be green, and a green strategic

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partnership is established with the supplier to achieve sustainable development. In general, one of the keys to building a green supply chain is to choose a suitable supplier.

The rest of this paper is organized as follows. In Section 2, an overview of the existing researches on supplier evaluation in GSC is provided. In Section 3, an adaptive weight D-S evidence theory model based on fuzzy-rough-sets-AHP method is put forward for supplier evaluation in GSC. In Section 4, a bearing cage supplier evaluation case is given. At last, this paper is concluded in Section 5.

2. Literature Review

A lot of significant studies on supplier evaluation in GSC are seen in the existing literatures. The representative research mainly focuses on two aspects as follows.

One is application of single method to the supplier evaluation problem. Buyukozkan and Cifci [6] proposed a fuzzy analytic network process (ANP) method based on multi-person decision-making schema under incomplete preference relationships for vendor selection. Based on the application of rough set theory to study the relations among organizational properties, supplier development program involvement properties, and performance outcome properties, Bai and Sarkis [7] put forward a formal model for green supplier selection. Tseng and Chiu [8] determined the weights of criteria and alternatives according to both by qualitative and quantitative information and sorted alternative suppliers based on a grey relational analysis (GRA). To obtain the best green supplier for a plastic manufacturing company in Singapore, Kannan et al. [9] put forward a fuzzy axiomatic design (FAD) method. To evaluate environmental performance of suppliers, Awasthi et al. [10] proposed a fuzzy multi-criteria method (FmCM). By adding green criteria into the criteria framework of supplier selection, Yeh and Chuang [11] proposed an optimum mathematical planning model (OMPM) for green partner selection. Wu et al. [12] proposed a fuzzy linguistic decision-making method to solve the problem of selecting green supplier.

The other is integrated application of two or more than two methods for supplier evaluation. Li and Zhao [13] built the assessment model by using threshold method and gray correlation analysis (GCA) for vehicle component supplier selecting. Yan [14] used genetic algorithm (GA) and AHP to realize the dynamic adjustment of index weights in green supplier selection. Kuo et al. [15] proposed a hybrid approach based on artificial neural network (ANN), data envelopment analysis (DEA), and ANP for green supplier selection. Kuo and Lin [16] put forward a supplier selection approach based on ANP and DEA with the consideration of green indicators due to environmental protection issues. Based on fuzzy decision-making trial and evaluation laboratory model (DEMATEL), ANP, and technique for order performance by similarity to ideal solution (TOPSIS), Buyukozkan and Cifci [17] proposed a hybrid fuzzy multi-criteria decision-making (MCDM) approach for green supplier evaluation. By combining AHP and TOPSIS, Luo and Peng [18] proposed an integrated model for both of evaluation and selection of green supplier.

The above two kinds of methods have theoretical basis and practical value, but they also have some limitations. The subjectivity of fuzzy AHP in determining the index weight is too large. Neural network calculation process is complex, redundant, which will result in lack of accurate calculation. TOPSIS method has the advantages of convenient calculation and strong applicability, but the evaluation process may be missing information and the results are not objective enough. Additionally, each evaluation expert is required to give personal subjective evaluation information when considering the same evaluation index set. When different evaluation experts compare multiple indicators on the same level, it is easy to appear contradictory or chaotic judgment and evaluation. Because of the limitations of evaluation experts' understanding of supplier capabilities, the evaluation index value is often characterized by uncertainty and incompleteness. Moreover, the evaluation index weight is obviously variable when the demand has changed or the preference of the evaluation experts is different.

Therefore, we proposed an adaptive weight D-S theory model in this paper to solve the uncertainty and incompleteness problems of index value of supplier evaluation in GSC. The adaptive weight of evaluation index is determined by our designed fuzzy-rough-sets-AHP method.

3. Adaptive Weight D-S Theory Model for Supplier Evaluation

3.1 Establishment of Index Framework

For supplier evaluation in green supply chain, to build a comprehensive index framework is of great significance. On the one hand, product attribute is the main ability embodiment of a supplier; on the other, comprehensive ability can give a strong support to the product attribute of a supplier. Here, the comprehensive ability mainly contains internal competitiveness, external competitiveness, and cooperation ability.

For internal competitiveness, it mainly can be divided into innovation ability, manufacturing capacity and agility. Because a supplier is not isolated in supply chain, it is unavoidably limited by its external competitiveness. For external competitiveness, it mainly can be divided into economic environment, geographical environment, social environment, and legal environment. For cooperation ability, it mainly can be divided into technical compatibility degree, cultural compatibility degree, information platform compatibility degree and reputation.

Therefore, the index framework of supplier evaluation in GSC is built as shown in Fig. 1. It can be represented as a criterion set $\{C_1, C_2, C_3, C_4\}$. Here, C_1 stands for product attribute, C_2 stands for internal competitiveness, C_3 stands for external competitiveness, and C_4 stands for cooperation ability. Among them, $C_1=\{C_{11}, C_{12}, C_{13}, C_{14}\}$. In other words, C_1 is divided into four indexes: C_{11}, C_{12}, C_{13}, and C_{14}. Here, C_{11} stands for cost, C_{12} stands for quality, C_{13} stands for service, and C_{14} stands for flexibility.

Four criterions are divided into two types as follows. (1) Comprehensive qualitative type: C_1. (2) Quantitative type: C_2, C_3, and C_4. For comprehensive qualitative type criterion, its value is determined by its subordinate indexes. For quantitative type criterion, its value is obtained by expert score method. Similarly, four indexes of C_1 are divided into two types as follows. (1) Quantitative type: C_{11} and C_{12}. (2) Direct qualitative type: C_{13} and C_{14}.

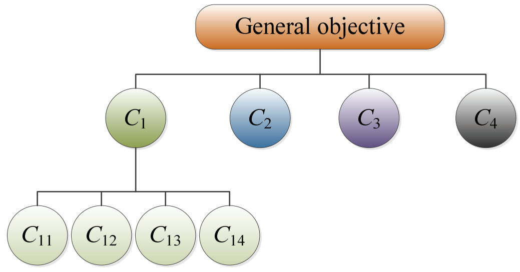

Fig. 1. The index framework.

3.2 Determination of the Adaptive Weight

The AHP method [19], which was put forward by Thomas L. Saaty, can not only make clear the hierarchical structure of the components of complex problem, but also verify the consistency of the results. Therefore, it has been widely applied in the weighting of multi-attribute decision-making problem [20-22]. The traditional AHP uses exact numbers to represent the relative importance between indexes. The evaluation of relative importance between indexes in supplier evaluation by experts depends on personal judgment and subjective experience, so using exact numbers to represent the relative importance between indexes is unjustified to some extent.

Fuzzy number can give expression to the connatural uncertainty of expert's preference. Additionally, the evaluation of relative importance between indexes by multiple experts is obviously indistinguishable when integrating the opinions of all experts. Instead of a membership function, rough boundary interval [21,23] can represent the indistinguishability as a set boundary area. It can better integrate the opinions of all evaluation experts. Accordingly, a fuzzy-rough-sets-AHP method is designed to solve the adaptive weight of evaluation index.

We use U to represent a domain which is actually a nonempty finite set of objects. Y is any object in U. In U, all objects are divided into n partitions: $S_1,S_2,\ldots,S_n$. If these n partition has the order of $S_1<S_2<\ldots<S_n$, the upper and lower approximation sets of any partition S_i ($1\leq i\leq n$) can be defined as follows:

$$\begin{aligned} \overline{AS}(S_i) &= \{Y \in K \mid K \subseteq U/R(Y) \wedge K \geq S_i\} \\ \underline{AS}(S_i) &= \{Y \in K \mid K \subseteq U/R(Y) \wedge K \leq S_i\} \end{aligned} \tag{1}$$

where $U/R(Y)$ represents the partition of the indistinct relationship $R(Y)$ in U.

According to the above definition, any ambiguous partition S_i in U can be represented by its rough boundary interval $RN(S_i)$. $RN(S_i)$ consists of its rough lower limit $\underline{L}(S_i)$ and rough upper limit $\overline{L}(S_i)$ which are defined as follows:

$$\underline{L}(S_i) = \frac{\sum_{Y \in \underline{AS}(S_i)} R(Y)}{\underline{N}(S_i)} \tag{2}$$

$$\overline{L}(S_i) = \frac{\sum_{Y \in \overline{AS}(S_i)} R(Y)}{\overline{N}(S_i)} \tag{3}$$

where $\overline{N}(S_i)$ is the number of objects in the upper approximation set of S_i and $\underline{N}(S_i)$ is the number of objects in the upper approximation set of S_i.

As can be seen, an ambiguous partition in the domain can be represented by a rough boundary interval containing a rough lower limit and a rough upper limit as follows:

$$RN(S_i) = \left[\underline{L}(S_i), \overline{L}(S_i)\right] \tag{4}$$

We start from the bottom layer of index framework shown in Fig. 1. There are q experts. The index set is $\{C_{11}, C_{12}, \ldots, C_{1l}\}$. Here, l=4.

Step 1: According to the evaluation of expert k (k=1,2,...,q) on $\{C_{11}, C_{12}, \ldots, C_{1l}\}$, the fuzzy reciprocal judgment matrix E^k is constructed as follows:

$$E^k = \begin{bmatrix} (1,1,1,1) & e_{1,2}^k & \cdots & e_{1,l}^k \\ e_{2,1}^k & (1,1,1,1) & \cdots & e_{2,l}^k \\ \vdots & \vdots & & \vdots \\ e_{l,1}^k & e_{l,2}^k & \cdots & (1,1,1,1) \end{bmatrix} \tag{5}$$

where $e_{i,j}^k$ represents the score of supplier j compared to supplier i evaluated by expert k, here i,j=1,2,...,l and $i \neq j$. $e_{i,j}^k = (a_{i,j}^k, b_{i,j}^k, c_{i,j}^k, d_{i,j}^k)$ is a trapezoidal fuzzy number and $a_{i,j}^k, b_{i,j}^k, c_{i,j}^k$ and $d_{i,j}^k$ ($a_{i,j}^k \le b_{i,j}^k \le c_{i,j}^k \le d_{i,j}^k$) are all positive real numbers. Then we verify the consistency of E^k. If it is qualified, do the next step; otherwise, redo this step.

Step 2: E^k is split into a^k, b^k, c^k, d^k. The expression of a^k is as follows:

$$a^k = \begin{bmatrix} 1 & a_{1,2}^k & \cdots & a_{1,l}^k \\ a_{2,1}^k & 1 & \cdots & a_{2,l}^k \\ \vdots & \vdots & & \vdots \\ a_{l,1}^k & a_{l,2}^k & \cdots & 1 \end{bmatrix} \tag{6}$$

Step 3: Based on $a^1, a^2, \ldots, a^q$, the rough group decision matrix is constructed as follows:

$$a = \begin{bmatrix} 1 & a_{1,2} & \cdots & a_{1,l} \\ a_{2,1} & 1 & \cdots & a_{2,l} \\ \vdots & \vdots & & \vdots \\ a_{l,1} & a_{l,2} & \cdots & 1 \end{bmatrix} \tag{7}$$

where $a_{i,j} = \{a_{i,j}^1, a_{i,j}^2, \ldots, a_{i,j}^q\}$, here i,j=1,2,...,l and $i \neq j$.

The rough boundary interval of $a_{i,j}^k \in a_{i,j}$ (k=1,2,...,q) is obtained as follows:

$$RN(a_{i,j}^k) = \left[a_{i,j}^{k,-}, a_{i,j}^{k,+} \right] \tag{8}$$

where $a_{i,j}^{k,-}$ is the rough lower limit of $a_{i,j}^k$ in set $a_{i,j}$ and $a_{i,j}^{k,+}$ is the rough upper limit of $a_{i,j}^k$ in set $a_{i,j}$.

Therefore, the rough boundary interval of $a_{i,j}$ can be represented as follows:

$$RN(a_{i,j}) = \left\{ \left[a_{i,j}^{1,-}, a_{i,j}^{1,+} \right], \left[a_{i,j}^{2,-}, a_{i,j}^{2,+} \right], \cdots, \left[a_{i,j}^{q,-}, a_{i,j}^{q,+} \right] \right\} \tag{9}$$

Based on the operational rule of rough boundary interval, the average form of $RN(a_{i,j})$ is obtained as follows:

$$Avg\_RN(a_{i,j}) = \left[a_{i,j}^-, a_{i,j}^+ \right] = \left[\frac{\sum_{k=1}^{q} a_{i,j}^{k,-}}{q}, \frac{\sum_{k=1}^{q} a_{i,j}^{k,+}}{q} \right] \tag{10}$$

where $a_{i,j}^-$ is the rough lower limit of set $a_{i,j}$ and $a_{i,j}^+$ is the rough upper limit of set $a_{i,j}$.

Step 4: The rough judgement matrix is constructed as follows:

$$EA=\begin{bmatrix} 1 & Avg\_RN(a_{1,2}) & \cdots & Avg\_RN(a_{1,l}) \\ Avg\_RN(a_{2,1}) & 1 & \cdots & Avg\_RN(a_{2,l}) \\ \vdots & \vdots & & \vdots \\ Avg\_RN(a_{l,1}) & Avg\_RN(a_{l,2}) & \cdots & 1 \end{bmatrix} \tag{11}$$

EA is divided into EA^- and EA^+. Here, EA^- is the rough lower limit matrix and EA^+ is the rough upper limit matrix. EA^- and EA^+ are expressed as follows:

$$EA^-=\begin{bmatrix} 1 & a_{1,2}^- & \cdots & a_{1,l}^- \\ a_{2,1}^- & 1 & \cdots & a_{2,l}^- \\ \vdots & \vdots & & \vdots \\ a_{l,1}^- & a_{l,2}^- & \cdots & 1 \end{bmatrix}, EA^+=\begin{bmatrix} 1 & a_{1,2}^+ & \cdots & a_{1,l}^+ \\ a_{2,1}^+ & 1 & \cdots & a_{2,l}^+ \\ \vdots & \vdots & & \vdots \\ a_{l,1}^+ & a_{l,2}^+ & \cdots & 1 \end{bmatrix} \tag{12}$$

The eigenvectors corresponding to the maximum eigenvalues of EA^- and $EA^+$are obtained respectively as follows:

$$VA^-=\left[va_1^-,va_2^-,\cdots,va_l^-\right]^{\mathrm{T}}, VA_t^+=\left[va_1^+,va_2^+,\cdots,va_l^+\right]^{\mathrm{T}} \tag{13}$$

where va_i^- are the value of VA^- on the *i* (*i*=1,2,...,*l*) dimension and va_i^+ are the value of VA^+on the *i* (*i*=1,2,...,*l*) dimension.

Then, we can get that $ga_i=(|va_i^-|+|va_i^+|)/2$, and a set $GA=\{ga_1,ga_2,...,ga_l\}$ is obtained.

Step 5: We repeat steps 3 and 4, so $GB_t=\{gb_1,gb_2,...,gb_l\}$, $GC=\{gc_1,gc_2,...,gc_l\}$ and $GD=\{gd_1,gd_2,...,gd_l\}$ can be obtained. Then the adaptive weight of evaluation indexes C_{11}, C_{12}, …, C_{1l} with the trapezoidal fuzzy number form are $z_1=(ga_1,gb_1,gc_1,gd_1)$, $z_2=(ga_2,gb_2,gc_2,gd_2)$,..., $z_l=(ga_l,gb_l,gc_l,gd_l)$. Here we use gravity model appoach to convert $z_i=(ga_i,gb_i,gc_i,gd_i)$ (*i*=1,2,...,*l*) into real number r_i as follows:

$$r_i=\frac{[(gd_i)^2+gd_i\cdot gc_i+(gc_i)^2]-[(ga_i)^2+ga_i\cdot gb_i+(gb_i)^2]}{3(gd_i+gc_i-ga_i-gb_i)} \tag{14}$$

We normalize r_1, r_2, ..., r_l and can obtain the adaptive weight of evaluation indexes C_{1i} as follows:

$$\omega(C_{1i})=\frac{\sum_{i=1}^{l} r_i}{l} \tag{15}$$

Step 6: For indexes C_1, C_2, C_3 and C_4, we repeat steps 1-5 and obtain the adaptive weights of them as $\omega(C_1),\omega(C_2),\omega(C_3),\omega(C_4)$.

3.3 D-S Theory Decision Regulations

By D-S theory, we can deal with the multi-criteria decision problems with uncertainty and incompleteness [24,25]. In the existing researches, it has been certified that a content result can be obtained and the uncertainty of decision can be decreased based on D-S theory [26-29]. According to

D-S theory, we define the suppliers to be evaluated $x_1, x_2, ..., x_i, ..., x_N$ as the D-S identification framework $\Theta = \{x_1, x_2, ..., x_i, ..., x_N\}$. All possible subsets of Θ can be expressed by power set 2^Θ. When all elements in Θ are incompatible and independent with each other, the number of elements in 2^Θ is 2^N. Then, a set function $m: 2^\Theta \to [0,1]$, which satisfies $m(\phi) = 0$ and $\sum_{A \subset \Theta} m(A) = 1$, is defined. Here, m is known as the basic probability allocation (BPA) function on Θ and A is a supplier to be evaluated. $m(A)$, which is the BPA value of A, represents the trust degree in A. Any supplier to be evaluated satisfying the condition $m(A)>0$ is called a focal element.

For $A \subseteq \Theta$, the fusion rule of finite BPA functions on Θ is as follows:

$$(m_1 \oplus m_2 \oplus ... \oplus m_n)(A) = \frac{1}{K} \sum_{A_1 \cap A_2 \cap ... \cap A_n = A} m_1(A_1) \cdot m_2(A_2) \cdot ... \cdot m_n(A_n) \tag{16}$$

K is the normalization constant and is expressed as follows:

$$K = \sum_{A_1 \cap A_2 \cap ... \cap A_n \neq \phi} m_1(A_1) \cdot m_2(A_2) \cdot ... \cdot m_n(A_n) = 1 - \sum_{A_1 \cap A_2 \cap ... \cap A_n = \phi} m_1(A_1) \cdot m_2(A_2) \cdot ... \cdot m_n(A_n) \tag{17}$$

The overall trust degree of A on Θ can be represented as a belief function $Bel(A) = \sum_{B \subseteq A} m(B)$ where $B \subset \Theta$, and the uncertainty degree of A on Θ can be represented as a plausible function $Pl(A) = \sum_{B \cap A \neq \phi} m(B)$ where $B \subset \Theta$.

For a supplier A on Θ, $Bel(A)$ shows the sum of the possibility estimate of all its subsets, and $Pl(A)$ shows the sum of the uncertainty estimate of all its subsets. For A, the degree of confirmation can be expressed by the trust interval $[Bel(A), Pl(A)]$.

According to the above analysis, the sum of credibility which the evidences support A is shown by $Bel(A)$ and the sum of credibility which the evidences does not negative A is shown by $Pl(A)$. Thus, the trust interval is formed as $[Bel(A), Pl(A)]$. The support degree to a supplier of belief function and plausible function can be reflected by $[Bel(A), Pl(A)]$ comprehensively.

According to references [30,31], to evaluate the suppliers by trust interval approach is more reasonable than max-belief-function decision-making approach or max-plausible-function decision-making approach. The D-S theory decision regulations based on trust interval for supplier evaluation in GSC are as follows.

(i) It is assumed that supplier A_i is better than supplier A_j with a degree of $P(A_i>A_j)$. The trust interval of A_i is $[Bel(A_i), Pl(A_i)]$, and the trust interval of A_j is $[Bel(A_j), Pl(A_j)]$. $P(A_i>A_j)$ is obtained as follows:

$$P(A_i > A_j) = \frac{\max[0, Pl(A_i) - Bel(A_j)] - \max[0, Bel(A_i) - Pl(A_j)]}{[Pl(A_i) - Bel(A_i)] + [Pl(A_j) - Bel(A_j)]} \tag{18}$$

where $P(A_i > A_j) \in [0,1]$.

(ii) The partial order relationship: (a) When $P(A_i>A_j)>0.5$, A_i is better than A_j, which is expressed as $A_i \succ A_j$; (b) When $P(A_i>A_j)<0.5$, A_i is worse than A_j, which is expressed as $A_i \prec A_j$; (c) When $P(A_i>A_j)=0.5$, there is no difference between A_i and A_j, which is expressed as $A_i = A_j$; (f) For three suppliers A_i, A_j and A_k, when $P(A_i>A_j)>0.5$ and $P(A_j>A_k)>0.5$, A_i is better than A_k, which is expressed as $A_i \succ A_j \succ A_k$.

3.4 Supplier Evaluation Based on D-S Theory

The weighted BPA value of focal element A_i ($i<2^N$) under index t ($t \in IF$), which is $\tilde{m}_t(A_i)$, is introduced into the D-S theory model as evidence input. The calculating and processing approaches for weighted BPA value of each focal element are as follows.

Based on investigating the actual status of each supplier, the expert gives the initial value of indexes which belongs to quantitative type or direct qualitative type. Here, the indexes which belong to definite quantitative type or direct qualitative type are assigned exact values, the indexes which are relatively fuzzy quantitative type are assigned value intervals, and the indexes which are completely unknown are assigned null value. By membership approach, we can calculate the tendency degree of the initial index value.

To an index, five levels of expert's remark are given as: $\{G_1,G_2,G_3,G_4,G_5\}$={very bad, bad, middle, good, very good}. Here, G_1 is the remark level corresponding to the minimum initial index value D_1, and G_5 is the remark level corresponding to the maximal initial index value D_5. However, to cost-based index C_{11}, G_1 is the remark level corresponding to the maximal initial index value D_1, and G_5 is the remark level corresponding to the minimum initial index value D_5.

We assume that the corresponding exact numbers of the five levels of expert's remark are: $E(G_1)=0$, $E(G_2)=0.25$, $E(G_3)=0.5$, $E(G_4)=0.75$, and $E(G_5)=1$. The membership degree of the initial index value to G_i is defined as β_i . On t, the tendency degree of A_i is expressed as $P_t(A_i)$, and the calculation of $P_t(A_i)$ is divided into two circumstances as follows:

(1) Index t belongs to quantitative type.

In this circumstance, the initial index value of A_i on t is a point-value a or an value-interval $[a,b]$.

If $D_i \le a \le D_{i+1}$ or $D_i \le a \le b \le D_{i+1}$, $P_t(A_i) = \beta_i E(G_i) + \beta_{i+1} E(G_{i+1})$.

If $D_i \le a \le D_{i+1}$ and $D_{i+1} \le b \le D_{i+2}$, $P_t(A_i) = \beta_i E(G_i) + \beta_{i+1} E(G_{i+1}) + \beta_{i+2} E(G_{i+2})$.

If $D_i \le a \le D_{i+1}$ and $D_j \le b \le D_{j+1}$, $P_t(A_i) = \beta_i E(G_i) + \beta_{i+1} E(G_{i+1}) + \ldots + \beta_j E(G_j) + \beta_{j+1} E(G_{j+1})$.

(2) Index t belongs to direct qualitative type.

In this circumstance, the tendency degree of A_i on t is equal to the number corresponding to the remark level.

By the above approach, the tendency degree of each focal element except Θ under any index can be solved. Here, the expert's uncertainty is indicated by Θ. Without the consideration of the influence of Θ, the supplier evaluation problem is a simple probability allocation problem. However, the advantages of D-S theory in solving multiple indexes decision problem are not reflected. Simultaneously, the trust degree of expert on any index is different and the uncertainty of an index is expressed by the probability allocation of Θ.

Thus, the probability allocation value of Θ on different indexes should also be considered differently. For example, in the supplier evaluation problem, the weight of evaluation index is obviously variable in different requirements. If cost reduction is needed, C_{11} will be more important and its trust degree should be larger. The BPA value of Θ on C_{11} should be smaller. Accordingly, we introduce the adaptive weight (determined in Section 3.2) to regulate the preference of each index and solve the probability allocation problem of Θ on all indexes, then the weighted BPA value of every focal element on any index is calculated as $\tilde{m}_t(A_i)$.

We assume that the adaptive weight of *t* is ω_t ($\omega_t \in (0,1)$). The bigger ω_t is, the higher the trust degree of expert to *t*, the lower the uncertainty of *t* is, and vice versa. Therefore, a weighted normalization processing of the BPA values of all focal elements is taken as follows:

$$\begin{cases} \tilde{m}_t(A_i) = \dfrac{\omega_t P_t(A_i)}{\sum_{i=1}^{l-1} P_t(A_i)} & A_i \neq \Theta \\ \tilde{m}_t(A_i) = 1 - \omega_t & A_i = \Theta \end{cases} \tag{19}$$

According to Fig. 1, the evidences of C_{11}, C_{12}, C_{13} and C_{14} of C_1 are fused and processed, and then the weighted BPA value of C_1 is calculated as $\tilde{m}_1(A_i)$. After that, we execute a secondary fusion which includes the weighted BPA value of C_1, C_2, C_3 and C_4, and the evaluation result of suppliers can be obtained.

4. Case Study

As an important part of modern mechanical equipment, the main function of bearing is to sustain the mechanical revolving body, depress the friction in movement and ensure the rotary precision. A bearing manufacturing enterprise has three candidate bearing-cage suppliers. To select the optimal bearing-cage supplier, supplier evaluation should be executed.

Firstly, the adaptive weight of evaluation index is determined by our designed fuzzy-rough-sets-AHP method. Four experts (expert 1, expert 2, expert 3, and expert 4) participate in the judgment on C_{11}, C_{12}, C_{13}, and C_{14}. Using the proportional scale method of trapezoidal fuzzy number [21], the trapezoidal-fuzzy-number reciprocal judgment matrices E^1, E^2, E^3, and E^4 are shown as follows.

$$E^1 = \begin{bmatrix} \tilde{5}/\tilde{5} & \tilde{6}/\tilde{4} & \tilde{6}/\tilde{4} & \tilde{7}/\tilde{3} \\ \tilde{4}/\tilde{6} & \tilde{5}/\tilde{5} & \tilde{6}/\tilde{4} & \tilde{6}/\tilde{4} \\ \tilde{4}/\tilde{6} & \tilde{4}/\tilde{6} & \tilde{5}/\tilde{5} & \tilde{6}/\tilde{4} \\ \tilde{3}/\tilde{7} & \tilde{4}/\tilde{6} & \tilde{4}/\tilde{6} & \tilde{5}/\tilde{5} \end{bmatrix}, E^2 = \begin{bmatrix} \tilde{5}/\tilde{5} & \tilde{5}/\tilde{5} & \tilde{6}/\tilde{4} & \tilde{6}/\tilde{4} \\ \tilde{5}/\tilde{5} & \tilde{5}/\tilde{5} & \tilde{6}/\tilde{4} & \tilde{6}/\tilde{4} \\ \tilde{4}/\tilde{6} & \tilde{4}/\tilde{6} & \tilde{5}/\tilde{5} & \tilde{5}/\tilde{5} \\ \tilde{4}/\tilde{6} & \tilde{4}/\tilde{6} & \tilde{5}/\tilde{5} & \tilde{5}/\tilde{5} \end{bmatrix},$$

$$E^3 = \begin{bmatrix} \tilde{5}/\tilde{5} & \tilde{7}/\tilde{3} & \tilde{5}/\tilde{5} & \tilde{6}/\tilde{4} \\ \tilde{3}/\tilde{7} & \tilde{5}/\tilde{5} & \tilde{3}/\tilde{7} & \tilde{4}/\tilde{6} \\ \tilde{5}/\tilde{5} & \tilde{7}/\tilde{3} & \tilde{5}/\tilde{5} & \tilde{6}/\tilde{4} \\ \tilde{4}/\tilde{6} & \tilde{6}/\tilde{4} & \tilde{4}/\tilde{6} & \tilde{5}/\tilde{5} \end{bmatrix}, E^4 = \begin{bmatrix} \tilde{5}/\tilde{5} & \tilde{6}/\tilde{4} & \tilde{7}/\tilde{3} & \tilde{8}/\tilde{2} \\ \tilde{4}/\tilde{6} & \tilde{5}/\tilde{5} & \tilde{6}/\tilde{4} & \tilde{7}/\tilde{3} \\ \tilde{3}/\tilde{7} & \tilde{4}/\tilde{6} & \tilde{5}/\tilde{5} & \tilde{6}/\tilde{4} \\ \tilde{2}/\tilde{8} & \tilde{3}/\tilde{7} & \tilde{4}/\tilde{6} & \tilde{5}/\tilde{5} \end{bmatrix}$$

Taking E^1 for example, it can be converted to the following form:

$$E^1 = \begin{bmatrix} (1,1,1,1) & (1,11/9,13/7,7/3) & (1,11/9,13/7,7/3) & (3/2,13/7,3,4) \\ (3/7,7/13,9/11,1) & (1,1,1,1) & (1,11/9,13/7,7/3) & (1,11/9,13/7,7/3) \\ (3/7,7/13,9/11,1) & (3/7,7/13,9/11,1) & (1,1,1,1) & (1,11/9,13/7,7/3) \\ (1/4,1/3,7/13,2/3) & (3/7,7/13,9/11,1) & (3/7,7/13,9/11,1) & (1,1,1,1) \end{bmatrix}$$

After consistency check, E^1, E^2, E^3 and E^4 are all qualified. Then they are split, and a^1 is as follows:

$$a^1 = \begin{bmatrix} 1 & 1 & 1 & 3/2 \\ 3/7 & 1 & 1 & 1 \\ 3/7 & 3/7 & 1 & 1 \\ 1/4 & 3/7 & 3/7 & 1 \end{bmatrix}$$

Based on a^1, a^2, a^3 and a^4, the rough group-decision matrix is obtained as follows:

$$a = \begin{bmatrix} \{1,1,1,1\} & \{1,1,3/2,1\} & \{1,1,1,3/2\} & \{3/2,1,1,7/3\} \\ \{3/7,1,1/4,3/7\} & \{1,1,1,1\} & \{1,1,1/4,1\} & \{1,1,3/7,3/2\} \\ \{3/7,3/7,1,1/4\} & \{3/7,3/7,3/2,3/7\} & \{1,1,1,1\} & \{1,1,1,1\} \\ \{1/4,3/7,3/7,1/9\} & \{3/7,3/7,1,1/4\} & \{3/7,1,3/7,3/7\} & \{1,1,1,1\} \end{bmatrix}$$

In element $a_{1,4}$={3/2,1,1,7/3}, the upper approximation set of partition '3/2' is {3/2,7/3} and the lower approximation set of partition '3/2' is {3/2,1,1}, so $\underline{L}$ ('3/2')=(3/2+1+1)/3=1.17, $\overline{L}$ ('3/2')=(3/2+7/3)/2=1.92 and RN('3/2')=[1.17,1.92]. Similarly, RN('1')=[1,1.46], RN('7/3')=[1.46,2.33] and $RN(a_{1,4})$={[1.17,1.92],[1,1.46],[1,1.46],[1.46,2.33]}.

Thus, $Avg\_RN(a_{1,4})$=[1.16,1.79]. The rough boundary intervals in average form of other elements of a can be also calculated. The rough judgment matrix is constructed as follows:

$$EA = \begin{bmatrix} [1,1] & [1.03,1.22] & [1.03,1.22] & [1.16,1.79] \\ [0.38,0.74] & [1,1] & [0.67,0.95] & [0.72,1.17] \\ [0.38,0.74] & [0.50,0.90] & [1,1] & [1,1] \\ [0.23,0.38] & [0.38,0.74] & [0.46,0.68] & [1,1] \end{bmatrix}$$

Then EA is split into EA^- and EA^+. The eigenvector corresponding to the maximum eigen-value of EA^- is VA^-=[0.71,0.44,0.45,0.30]^T and the eigenvector corresponding to the maximum eigen-value of EA^+ is VA^+= [0.65,0.49,0.47,0.34]^T. So GA={0.68,0.47,0.46,0.32}. Similarly, GB={0.73,0.51,0.66,0.58}, GC={0.82,0.67,0.73,0.69} and GD={0.95,0.77,0.83,0.75}. Then the adaptive weight of indexes C_{11}, C_{12}, C_{13} and C_{14} with the trapezoidal fuzzy number form are z_1=(0.68,0.73,0.82,0.95), z_2 =(0.47,0.51,0.67,0.77), z_3=(0.46,0.66,0.73,0.83) and z_4=(0.32,0.58,0.69,0.75). After gravity model approach processing and normalization processing, we obtain the adaptive weight of evaluation indexes C_{11}, C_{12}, C_{13}, and C_{14}: $\omega(C_{11})$ =0.30, $\omega(C_{12})$ =0.23, $\omega(C_{13})$ =0.25, and $\omega(C_{14})$ =0.22. Similarly, the adaptive weights of criterions C_1, C_2, C_3, and C_4 are $\omega(C_1)$ =0.57, $\omega(C_2)$ =0.18, $\omega(C_3)$ =0.26, and $\omega(C_4)$ =0.09.

Secondly, we use the proposed adaptive weight D-S theory model to deal with the decision of supplier evaluation problem. For the three candidate suppliers, their initial index values are shown in Table 1.

Table 1. Initial index value

Supplier	C_1				C_2/ full score is 17	C_3/ full score is 9	C_4/ full score is 1
	C_{11}/¥	C_{12}/ error value (mm)	C_{13}	C_{14}			
x_1	6.4×10^1	0.01	Good	Very bad	15	[8.5, 9]	0.9848
x_2	1.9×10^3	0.01	Very good	Good	[15, 16]	[8.5, 9]	1
x_3	2.8×10^4	0.03	Very bad	Good	[5, 9]	/	1

Corresponding to the remark level $\{G_1,G_2,G_3,G_4,G_5\}$, the reference values of the index belonging to quantitative type are as follows: $G(C_{11})=\{10^5, 10^4, 10^3, 10^2, 10^1\}$, $G(C_{12})=\{0.05, 0.04, 0.03, 0.02, 0.01\}$, $G(C_2)=\{17, 13, 9, 5, 1\}$, $G(C_3)=\{1, 3, 5, 7, 9\}$ and $G(C_4)=\{0, 0.25, 0.5, 0.75, 1\}$.

Then, the membership degree of initial index value to every remark level is obtained. The data in Table 1 is translated into the membership degree form corresponding to remark grade. As shown in Table 2, the tendency degree form of initial index value is obtained.

Table 2. The tendency degree form of initial index value

Supplier	C_{11}	C_{12}	C_{13}	C_{14}	C_2	C_3	C_4
x_1	0.8500	1.0000	0.7500	0	0.8750	0.9688	0.9848
x_2	0.4750	1.0000	1.0000	0.7500	0.8813	0.9688	1.0000
x_3	0.2000	0.3000	0	0.7500	0.3750	/	1.0000

We define the set of candidate suppliers as the D-S theory identification framework: $\Theta=\{x_1, x_2, x_3\}$. Here, x_1, x_2, and x_3 represent bearing-cage suppliers 1, 2, and 3, respectively.

For four indexes C_{11}, C_{12}, C_{13}, and C_{14} and three criterions C_2, C_3, and C_4, the weighted BPA values of all focal elements are obtained according to the tendency degree shown in Table 2 and the weight vectors ($\omega(C_{11})$, $\omega(C_{12})$, $\omega(C_{13})$, $\omega(C_{14})$)=(0.30, 0.23, 0.25, 0.22), and ($\omega(C_2)$, $\omega(C_3)$, $\omega(C_4)$)=(0.18, 0.26, 0.09). The calculation result is as follows:

(1) C_{11}: $\tilde{m}_{11}(x_1)$ =0.1672, $\tilde{m}_{11}(x_2)$ =0.0934, $\tilde{m}_{11}(x_3)$ =0.0393, $\tilde{m}_{11}(\Theta)$ =0.7000.

(2) C_{12}: $\tilde{m}_{12}(x_1)$ =0.0920, $\tilde{m}_{12}(x_2)$ =0.0920, $\tilde{m}_{12}(x_3)$ =0.0460, $\tilde{m}_{12}(\Theta)$ =0.7700.

(3) C_{13}: $\tilde{m}_{13}(x_1)$ =0.1071, $\tilde{m}_{13}(x_2)$ =0.1429, $\tilde{m}_{13}(x_3)$ =0, $\tilde{m}_{13}(\Theta)$ =0.7500.

(4) C_{14}: $\tilde{m}_{14}(x_1)$ =0, $\tilde{m}_{14}(x_2)$ =0.1100, $\tilde{m}_{14}(x_3)$ =0.1100, $\tilde{m}_{14}(\Theta)$ =0.7800.

(5) C_2: $\tilde{m}_2(x_1)$ =0.0739, $\tilde{m}_2(x_2)$ =0.0744, $\tilde{m}_2(x_3)$ =0.0317, $\tilde{m}_2(\Theta)$ =0.8200.

(6) C_3: $\tilde{m}_3(x_1)$ =0.1300, $\tilde{m}_3(x_2)$ =0.1300, $\tilde{m}_3(\Theta)$ =0.7400

(7) C_4: $\tilde{m}_4(x_1)$ =0.0297, $\tilde{m}_4(x_2)$ =0.0302, $\tilde{m}_4(x_3)$ =0.0302, $\tilde{m}_4(\Theta)$ =0.9100.

After that, we take $\tilde{m}_{11}(x_i)$, $\tilde{m}_{12}(x_i)$, $\tilde{m}_{13}(x_i)$, and $\tilde{m}_{14}(x_i)$ as the evidence input and implement the first evidence fusion. The BPA values of all focal elements are obtained as follows: $m_1(x_1)$=0.1001, $m_1(x_2)$=0.7815, $m_1(x_3)$=0.0772, $m_1(x_1,x_2)$=0.0102, $m_1(x_2,x_3)$=0.0201, $m_1(x_1,x_3)$=0.0098, and $m_1(\Theta)$=0.0011.

We normalize BPA values $m_1(A_i)$ of the suppliers to be evaluated and Θ on index C_1. With the consideration of $\omega(C_1)$, the weighted BPA values are obtained as follows: $\tilde{m}_1(x_1)$ =0.0571, $\tilde{m}_1(x_2)$ =0.4455, $\tilde{m}_1(x_3)$ =0.0440, $\tilde{m}_1(x_1,x_2)$ 0.0058, $\tilde{m}_1(x_2,x_3)$ =0.0115 , $\tilde{m}_1(x_1,x_3)$ =0.0056, and $\tilde{m}_1(\Theta)$ =0.0006.

Then, we take $\tilde{m}_1(A_i)$, $\tilde{m}_2(A_i)$, $\tilde{m}_3(A_i)$ and $\tilde{m}_4(A_i)$ as the evidence input and implement the second evidence fusion. The comprehensive BPA values of all focal elements are obtained as follows: $m(x_1)$=0.1255, $m(x_2)$=0.7088, $m(x_3)$=0.0102, $m(x_1,x_2)$=0.0999, $m(x_2,x_3)$=0.0032, $m(x_1,x_3)$=0.0506 and $m(\Theta)$=0.0018。

$Bel(A_i)$ and $Pl(A_i)$ of all suppliers are calculated. Then the trust intervals of all suppliers are obtained as follows:

(1) x_1: [0.1255, 0.2778].

(2) x_2: [0.7088, 0.8137].

(3) x_3: [0.0102, 0.0658].

On the basis of the D-S theory decision regulations, the result is as follows:

(1) $P(x_1>x_2)=0$, so $x_1 \prec x_2$.

(2) $P(x_1>x_3)=1$, so $x_3 \prec x_1$

Therefore, the evaluation result of three suppliers is $x_3 \prec x_1 \prec x_2$ and supplier 2 is the optimal bearing-cage supplier. Thus, the proposed adaptive weight D-S theory model can solve the supplier evaluation problem in GSC even the initial index value is uncertain and incomplete (See in Table 1, the initial values of x_2 and x_3 on index C_2 are interval values and the initial value of x_3 on index C_3 is missing).

To verify the effectiveness of the proposed adaptive weight D-S theory model, we use traditional TOPSIS method [18,21] to make a comparison. Because the traditional TOPSIS method can only solve the evaluation problem with certain and complete index value, we replace the interval with its mid-value and ignore the index with missing index value (The initial values of x_2 and x_3 on index C_2 are 15.5 and 7, respectively. Index C_3 is ignored). The tendency degree method is still used to process the initial index value. Then, processing of the adaptive weights is executed on the basis of the hierarchical structure shown in Fig. 1 and the final weight vector of C_{11}, C_{12}, C_{13}, C_{14}, C_2, and C_4 is ω=(0.15, 0.11, 0.12, 0.09, 0.18, 0.09) in which index C_3 is ignored. In Table 3, the weighted index value matrix is obtained.

Table 3. The weighted index value matrix

Supplier	C_{11}	C_{12}	C_{13}	C_{14}	C_2	C_4
x_1	0.1275	0.1100	0.0900	0	0.1575	0.0886
x_2	0.0712	0.1100	0.1200	0.0675	0.1586	0.0900
x_3	0.0300	0.0330	0	0.0675	0.0675	0.0900

From Table 3, the positive and negative ideal points are (0.1275, 0.1100, 0.1200, 0.0675, 0.1586, 0.0900) and (0.0300, 0.0330, 0, 0, 0.0675, 0.0886), respectively. So we can obtain the close degree to positive ideal point of each supplier is as follows:

(1) x_1: 0.7065.

(2) x_2: 0.7686.

(3) x_3: 0.2569.

Therefore, the evaluation result of three candidate suppliers by traditional TOPSIS method is $x_3 \prec x_1 \prec x_2$ and the bearing manufacturing enterprise should choose supplier 2 as the optimal bearing cage supplier. The evaluation results of the proposed adaptive weight D-S theory model and traditional TOPSIS method are consistent. This shows that the proposed adaptive weight D-S theory model is feasible and effective.

5. Conclusion

In this paper, an adaptive weight D-S theory model is proposed for the evaluation problem characterized by uncertainty and incompleteness and variable index weight in GSC. In addition, a fuzzy-rough-sets-AHP approach is designed to obtain the adaptive index weight. The index framework is established considering of the main factors affecting the supplier evaluation in GSC, which can improve the scientific nature and rationality. The case study and the comparison with TOPSIS show that the optimal supplier of manufacturing enterprise can be correctly selected by the proposed adaptive weight D-S theory model.

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