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Fuzzy evaluation on supply chain competitiveness based on membership degree transformation new algorithm

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ABSTRACT

Supply chain is a large complex system. It is composed of multiple related enterprises, the competitiveness of which is determined by various factors. The core of fuzzy evaluation is membership degree transformation. The new algorithm: using data mining technology based on entropy to mine knowledge information about object classification hidden in every index, affirm the relationship of object classification and index membership, eliminate the redundant data in index membership for object classification by defining distinguishable weight and extract valid values to compute object membership. The paper applied the new algorithm in fuzzy evaluation on supply chain competitiveness.

Key words: Supply chain competitiveness, Membership degree transformation, Fuzzy evaluation

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INTRODUCTION

Warren Hausman pointed out that the current competition is no longer a competition between enterprises, but a competition between supply chains [1]. How to evaluate supply chain competitiveness caused more and more attention. In the work of [2] the sources of competitiveness and the strategies of improvement in supply chain were further discussed. The primary methods and evaluation indexes of supply chain evaluation were summed up and analyzed in [3]. A supply chain competitiveness evaluation system was built from the perspective of game theory in [4]. Logistics element capacity and logistics operation capability have prominent influence on supply chain competitiveness from [5]. In the work of [6], Mingfang Li built a supply chain competitiveness evaluation index system from agility, close relationship, customer orientation, management level, competitiveness of core enterprises based on [7-9]. Fuzzy comprehensive evaluation method was applied in evaluating single supply chain competitiveness in [10].

The basic conditions of fuzzy evaluation are determining the importance weights of sub-indexes and the membership degree vectors of end indexes. However, in order to get reliable evaluation result, it also need correct calculation. The core of fuzzy evaluation is membership degree transformation calculation. But the existing transformation methods including the method in [6] should be questioned, because redundant data in index membership degree is also used to calculate object membership degree, which is not useful for object classification. A kind of filter from the viewpoint of objective classification method is designed to identify and remove those redundant index memberships as well as the redundant data in the index membership [11]. The evaluation model of the library's knowledge capital based on the transformation of degree of membership was put forward in [12]. The performance of the green supply chain was evaluated with the conversion algorithm of membership to improve the shortage of green supply chain and improve performance level in [13].

The new algorithm: using data mining technology based on entropy to mine knowledge information about object classification hidden in every index, affirm the relationship of object classification and index membership, eliminate the redundant data in index membership for object classification by defining distinguishable weight and extract valid values to compute object membership. The paper will apply the new algorithm in the fuzzy evaluation on supply chain competitiveness.

THE NEW ALGORITHM OF MEMBERSHIP DEGREE TRANSFORMATION- $M(1,2,3)$

The distinguishable weight

Based on the fuzzy appraisal steps, the membership degree is known.

① Assume that $\mu_{j1}(Q) = \mu_{j2}(Q) = \cdots = \mu_{jp}(Q)$, then *j*th index membership implies that the probability of classifying object *Q* into every grade is equal. Obviously, this information is of no use to the classification of object Q. Deleting *j*th index will not affect classification. Let $\alpha_j(Q)$ represent the normalized and quantized value describing *j*th index contributes to classification, then in this case $\alpha_j(Q) = 0$.

② If there exists an integer *k* satisfying $\mu_{jk}(Q) = 1$ and other memberships are zero, then *j*th index membership implies that *Q* can be only classified into C_k. In this case, *j*th index contributes most to classification and $\alpha_j(Q)$ should obtain its maximum value.

③ Similarly, if $\mu_{jk}(Q)$ is more concentrated for *k*, *j*th index contributes more to classification, i.e., $\alpha_j(Q)$ is larger. Conversely, if $\mu_{jk}(Q)$ is more scattered for *k*, *j*th index contributes less to classification, i.e., $\alpha_j(Q)$ is smaller.

The above ①~③ show that $\alpha_j(Q)$, reflecting the value that *j*th index contributes to classification, is decided by the extent $\mu_{jk}(Q)$ is concentrated or scattered for *k*. And it can be described quantitatively by the entropy $H_j(Q)$. Therefore, $\alpha_j(Q)$ is a function of $H_j(Q)$.

$$H_j(Q) = -\sum_{k=1}^{p} \mu_{jk}(Q) \cdot \log \mu_{jk}(Q) \tag{1}$$

$$v_j(Q) = 1 - \frac{1}{\log p} H_j(Q) \tag{2}$$

$$\alpha_j(Q) = v_j(Q) \Big/ \sum_{t=1}^{m} v_t(Q) \quad (j = 1 \sim m) \tag{3}$$

Definition 1

If $\mu_{jk}(Q)\,(k = 1 \sim p,\ j = 1 \sim m)$ *is the membership of jth index belonging to* C_k *and satisfies Eq. (1); by (1), (2), (3),* $\alpha_j(Q)$ *is called distinguishable weight of* j *th index corresponding to* Q. *Obviously,* $\alpha_j(Q)$ *satisfies:*

$$\sum_{j=1}^{m} \alpha_j(Q) = 1 \tag{4}$$

The effective value

The significance of $\alpha_j(Q)$ lies in its "distinguishing" function, i.e., it is a measure that reveals the exactness of object *Q* being classified by *j*th index membership and even the extent of the exactness. If $\alpha_j(Q) = 0$, from the properties of entropy, then $\mu_{j1}(Q) = \mu_{j2}(Q) = \cdots = \mu_{jp}(Q)$. This implies *j*th index membership is redundant and useless for classification. Naturally the redundant index membership can't be utilized to compute membership of object *Q*.

Definition 2
Suppose that there are m indexes which affect object Q, where the importance weights $\lambda_j(Q)$ *of* $(j = 1 \sim m)$ *index about object Q is given and satisfies:*

$$0 \le \lambda_j(Q) \le 1 \, , \sum_{j=1}^{m} \lambda_j(Q) = 1 \tag{5}$$

If $\mu_{jk}(Q)$ $(k = 1 \sim p, j = 1 \sim m)$ *is the membership of jth index belonging to* C_k *and satisfies Eq.(5), and* $\alpha_j(Q)$ *is the distinguishable weight of jth index corresponding to* Q *, then*

$$\alpha_j(Q) \cdot \mu_{jk}(Q) \, , (k = 1 \sim p) \tag{6}$$

is called effective distinguishable value of kth class membership of jth index.

The comparable value
Definition 3
If $\alpha_j(Q) \cdot \mu_{jk}(Q)$ *is kth class effective value of jth index, and* $\beta_j(Q)$ *is importance weight of jth index related to object* Q *,*

$$\beta_j(Q) \cdot \alpha_j(Q) \cdot \mu_{jk}(Q) \qquad (k = 1 \sim p) \tag{7}$$

is called comparable effective value of kth class membership of jth index, or kth class comparable value for short. Clearly, kth class comparable values of different indexes are comparable between each other and can be added directly.

Definition 4
If $\beta_j(Q) \cdot \alpha_j(Q) \cdot \mu_{jk}(Q)$ *is kth class comparable value of jth index of Q, where* $(j = 1 \sim m)$ *, then:*

$$M_k(Q) = \sum_{j=1}^{m} \beta_j(Q) \cdot \alpha_j(Q) \cdot \mu_{jk}(Q) \quad (k = 1 \sim p) \tag{8}$$

is named kth class comparable sum of object Q.

Obviously, the bigger $M_k(Q)$ is, the more possibly that object *Q* belongs to C_k.

Definition 5
If $M_k(Q)$ *is kth class comparable sum of object, and* $\mu_k(Q)$ *is the membership of object Q belonging to* C_k*, then:*

$$\mu_k(Q) \stackrel{\Delta}{=} M_k(Q) \Big/ \sum_{t=1}^{p} M_t(Q) \; (k = 1 \sim p) \tag{9}$$

Obviously, given by Eq.(9), membership degree $\mu_k(Q)$ *satisfies:*

$$0 \le \mu_k(Q) \le 1, \; \sum_{k=1}^{p} \mu_k(Q) = 1 \tag{10}$$

Up to now, supposing that index membership and index importance weight are given, by Eq. (1), (2), (3), (6), (7), (8), (9), the transformation from index membership to object membership is realized. And this transformation needs no prior knowledge and doesn’t cause wrong classification information.

The above membership transformation method can be summarized as “effective, comparison and composition”, which is denoted as $M(1,2,3)$.

CASE ANALYSIS

The fuzzy evaluation matrix of supply chain competitiveness

According to [6], we can obtain the fuzzy evaluation matrix of supply chain competitiveness, as Table 1 shows. In the table, the values in brackets behind corresponding indexes are their importance weights; the vectors behind the base indexes are their membership vectors including five grades: C_1(very strong), C_2(stronger), C_3(general), C_4(weaker), C_5(very weak).

Table 1. The index data of supply chain competitiveness

The goal	The criterion level	The factor level	Membership vectors (C_1, C_2, C_3, C_4, C_5)
Supply chain competitiveness	Supply chain agility A_1(0.25)	Time to market of new product B_{11}(0.20)	(0.20, 0.35, 0.25, 0.10, 0.10)
		Output flexibility B_{12}(0.25)	(0.15, 0.30, 0.25, 0.20, 0.10)
		Delivery flexibility B_{13}(0.30)	(0.10, 0.30, 0.10, 0.35, 0.15)
		Manufacturing lead time B_{14}(0.25)	(0.15, 0.35, 0.25, 0.20, 0.05)
	Supply chain close relationship A_2(0.15)	System production and demand rate B_{21}(0.25)	(0.20, 0.25, 0.15, 0.20, 0.20)
		Suppliers business rate of core enterprises B_{22}(0.30)	(0.20, 0.35, 0.20, 0.15, 0.10)
		Distributors business rate of core enterprise B_{23}(0.25)	(0.30, 0.35, 0.15, 0.10, 0.10)
		Supply chain communicating level B_{24}(0.20)	(0.30, 0.30, 0.15, 0.15, 0.10)
	Customer orientation A_3(0.20)	Customized products yield rate B_{31}(0.25)	(0.20, 0.25, 0.15, 0.25, 0.15)
		Customers satisfaction B_{32}(0.30)	(0.10, 0.35, 0.20, 0.25, 0.10)
		Punctual delivery order rateB_{33}(0.30)	(0.20, 0.35, 0.25, 0.15, 0.05)
		customers retention B_{34}(0.15)	(0.15, 0.20, 0.30, 0.25, 0.10)
	Supply chain management level A_4(0.20)	Production percent of pass B_{41}(0.15)	(0.30, 0.20, 0.20, 0.20, 0.10)
		Inventory turnover rate B_{42}(0.20)	(0.40, 0.20, 0.25, 0.10, 0.05)
		Holding costs rate B_{43}(0.40)	(0.35, 0.40, 0.15, 0.10, 0.00)
		Total order cycle B_{44}(0.25)	(0.10, 0.15, 0.35, 0.25, 0.15)
	Competitiveness of core enterprises A_5(0.20)	Cultural affinity B_{51}(0.30)	(0.20, 0.40, 0.15, 0.15, 0.10)
		Profitability B_{52}(0.35)	(0.30, 0.45, 0.20, 0.05, 0.00)
		Market controlling ability B_{53}(0.10)	(0.20, 0.35, 0.20, 0.15, 0.10)
		Informatization level B_{54}(0.25)	(0.15, 0.35, 0.30, 0.15, 0.05)

Fuzzy evaluation steps based on M(1,2,3) model

(1) Take Supply chain agility A_1 as an example. The calculation steps of its membership vector are:

① A_1 includes four indexes $B_{11} \sim B_{14}$, the $U(A_1)$ is:

$$U(A_1)=\begin{pmatrix} 0.20 & 0.35 & 0.25 & 0.10 & 0.10 \\ 0.15 & 0.30 & 0.25 & 0.20 & 0.10 \\ 0.10 & 0.30 & 0.10 & 0.35 & 0.15 \\ 0.15 & 0.35 & 0.25 & 0.20 & 0.05 \end{pmatrix}$$

According to the jth row $j(j=1\sim 4)$ of $U(A_1)$, the distinguishable weights of B_{1j} are obtained and the distinguishable weight vector is: $\alpha(A_1)=(0.2496 \quad 0.1434 \quad 0.2997 \quad 0.3073)$.

②In Table 1, the importance weight vector of $B_{11} \sim B_{14}$ is: $\beta(A_1)=(0.20 \quad 0.25 \quad 0.30 \quad 0.25)$

③Calculate the kth comparable value of B_{1j} $(j=1,2,3,4)$ and obtain the comparable value matrix $N(A_1)$ of A_1:

$$N(A_1)=\begin{pmatrix} 0.0100 & 0.0175 & 0.0125 & 0.0050 & 0.0050 \\ 0.0054 & 0.0108 & 0.0090 & 0.0072 & 0.0036 \\ 0.0090 & 0.0270 & 0.0090 & 0.0315 & 0.0135 \\ 0.0115 & 0.0269 & 0.0192 & 0.0154 & 0.0038 \end{pmatrix}$$

④According to $N(A_1)$, calculate the kth comparable sum of A_1 and obtain the comparable sum vector:

$M(A_1) = (0.0359 \quad 0.0821 \quad 0.0496 \quad 0.0590 \quad 0.0259)$

⑤According to $M(A_1)$, calculate the membership vector $\mu(A_1)$ of A_1:

$\mu(A_1) = (\ 0.1421 \quad 0.3251 \quad 0.1966 \quad 0.2336 \quad 0.1026)$

In the same steps, we can calculate $\mu(A_2)$, $\mu(A_3)$, $\mu(A_4)$ and $\mu(A_5)$, which, with $\mu(A_1)$, form the evaluation matrix $U(S)$ of supply chain competitiveness:

$$U(S) = \begin{pmatrix} \mu(A_1) \\ \mu(A_2) \\ \mu(A_3) \\ \mu(A_4) \\ \mu(A_5) \end{pmatrix} = \begin{pmatrix} 0.1421 & 0.3251 & 0.1966 & 0.2336 & 0.1026 \\ 0.2646 & 0.3350 & 0.1657 & 0.1307 & 0.1040 \\ 0.1577 & 0.3272 & 0.2299 & 0.2045 & 0.0807 \\ 0.3293 & 0.3286 & 0.1922 & 0.1204 & 0.0294 \\ 0.2544 & 0.4210 & 0.2096 & 0.0869 & 0.0281 \end{pmatrix}$$

(2) According to $U(S)$ and the weights of each criteria in the criterion level, we can calculate the final membership vector $\mu(S)$ of the goal S:

$$\mu(S) = (\mu_1(S), \cdots, \mu_5(S)) = (0.2503 \quad 0.3621 \quad 0.2011 \quad 0.1343 \quad 0.0521)$$

Recognition

Because the evaluation grades of supply chain competitiveness are orderly, that is, C_k is superior to C_{k+1}, so we apply confidence recognition rule to determine the grade of supply chain competitiveness:

Let $\lambda(\lambda > 0.6)$ is the confidence,

$$K_0 = \min\left\{ k \left| \sum_{t=1}^{k} \mu_t(S) \geq \lambda, 1 \leq k \leq 5 \right. \right\}$$

S belongs to the K_k *th* grade, of which the confidence degree is no lower than $\sum_{t=1}^{k} \mu_t(S)$.

In the example, according to the final membership vector $\mu(S)$, we can judge that *S* belongs the C_2 (stronger), with the confidence degree 61% (0.2503 +0.3621=0.6124).

RESULT ANALYSIS

We have applied $M(1,2,3)$ to judge the supply chain competitiveness as C_2 (stronger), with confidence degree 61%. But the supply chain competitiveness is judged as C_2 (stronger) only with the confidence degree 50%(0.2056+0.2968=0.5024). Clearly, accuracy of evaluation is improved by defining index distinguishable weight to remove the redundant data of target classification in index membership degree.

However, the confidence degree to judge supply chain competitiveness as “very strong” is 25.03%, it is far less than degree “very strong”. Although, the supply chain competitiveness is judged as “stronger”, the confidence degree is not so high (61%). So, the supply chain competitiveness needs to be improved.

According to *U(S)*, the confidence degrees judged as “stronger” of A_1 (supply chain agility) and A_3 (customer orientation) are 46.72% and 48.49% respectively. They are the two main respects affecting supply chain competitiveness which should be strengthened specially. Then the confidence degrees judged as “stronger” of A_2 (Supply chain close relationship) is less than 60%. It should also be paid attention to.

CONCLUSION

The transformation of membership degree is the key computation of fuzzy evaluation for multi-indexes fuzzy decision-making, but the existing transformation methods have some questions. The paper analyzes the reasons of the questions, obtains the solving method, and at last builds the $M(1,2,3)$ model without the interference of redundant data, which is different from $M(\bullet,+)$ and is a nonlinear model.

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