

Selection Method of Evaluation Indicators with Three-Parameter Interval Grey Number

Fanlin Meng, Na Wang, Bingjun Li*

College of Information and Management Science, Henan Agricultural University, Zhengzhou, China Email: fanlin_meng@163.com, sqiuwangna@163.com, ^{*}zzlbjun@163.com

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Abstract

The evaluation problem with three-parameter interval grey number (T-PIGN) widely exists in real world. To select effective evaluation indicators of the problem, this paper puts forward evaluation index system selection principle of T-PIGN based on distance entropy model, and gives out evaluation index system selection judgment criterion of T-PIGN. Furthermore, for the redundancy of evaluation index system with T-PIGN, a selection method of evaluation index system with T-PIGN is proposed. Finally, the applicability of the proposed method is verified by concrete examples.

Keywords

Evaluation Indicators Selection, Three-Parameter Interval Grey Number, Grey Distance Entropy

1. Introduction

The comprehensiveness and proper simplification of evaluation index system is an important and key step in multiple attributes evaluation problem. Although, there are many influencing factors on the evaluation effectiveness of evaluation objects, the evaluation index is not the more the better. The key problem of evaluation is whether the selected index is proper and reasonable. The omission of important index and the overlap of index information will make the evaluation result distorted, and too many evaluation indexes will increase the unnecessary workload and difficulty of the quantitatively calculation. Therefore, scientifically establishing the evaluation index system is an important part of the evaluation problem. There are a lot of achievements in this aspect [1]-[5]. According to the methods and properties, the index selection method can be divided into qualitative method, quantitative method and comprehensive method [6]. Zhang *et al.* put forward a simple and feasible method

^{*}Corresponding author.

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that directly applies the basic principle of principle component and combines qualitative analysis with quantitative analysis to screen the economic index [7]. Li Chongming and Ding Lieyun gave a method to turn a system into a graph and formulated a model to select system core by using the cluster analysis and grey correlative analysis [8]. Li Yuanyuan, Yun Jun and Zhang Chaoyang proposed an indicator selection method based on attribute significance of rough set [9] [10]. These achievements provide technical support for constructing evaluation index system scientifically at different angles.

In reality, evaluation index with three-parameter interval grey number (T-PIGN) exists widely, and there are many scholars studying this problem. Li *et al.* proposed a risky evaluation approach based on prospect theory to solve the multi-criteria evaluation problem with T-PIGN [11]. Wang Jiefang and Liu Sifeng proposed the definition of relative superiority degree between T-PIGN and the real numbers, and gave two types of algebraic expression [12]. Wang *et al.* put forward a multi-index grey-target evaluation method based on grey lational entropy to solve the multi-index evaluation problems with T-PIGN [13]. However, there are fewer researches that involved in the selection of existing evaluation index system with T-PIGN. Therefore, this paper attempts to construct distance entropy model of T-PIGN based on the information entropy theory, and to provide a method to select the evaluation index system with T-PIGN.

2. Grey Distance Entropy Model Based on Three-Parameter Interval Grey Number

2.1. Three-Parameter Interval Grey Number

Definition 1: $x(\bigotimes) \in [x^L, x^*, x^U] (0 \prec x^L \leq x^* \leq x^U)$ is called the T-PIGN, where x^L and x^U are the lower and upper bounds; x^* is the center of gravity, namely the most possible data point.

Define the operation of T-PIGN, which is similar to the operation properties of the interval grey number. Let

$$a(\otimes) \in \left[a^{L}, a^{*}, a^{U}\right] \left(0 \prec a^{L} \leq a^{*} \leq a^{U}\right) \text{ and } b(\otimes) \in \left[b^{L}, b^{*}, b^{U}\right] \left(0 \prec b^{L} \leq b^{*} \leq b^{U}\right)$$

be the T-PIGN, we define:

$$a(\otimes) + b(\otimes) = \left[a^{L} + b^{L}, a^{*} + b^{*}, a^{U} + b^{U}\right]$$
$$a(\otimes) - b(\otimes) = \left[a^{L} - b^{U}, a^{*} - b^{*}, a^{U} - b^{L}\right]$$
$$a(\otimes) \cdot b(\otimes) = \left[\min\left(a^{L}b^{L}, a^{L}b^{U}, a^{U}b^{L}, a^{U}b^{U}\right), a^{*}b^{*}, \max\left(a^{L}b^{L}, a^{L}b^{U}, a^{U}b^{L}, a^{U}b^{U}\right)\right]$$
$$\frac{a(\otimes)}{b(\otimes)} = \left[a^{L}, a^{*}, a^{U}\right] \left[\frac{1}{b^{U}}, \frac{1}{b^{*}}, \frac{1}{b^{L}}\right]$$

2.2. Three-Parameter Interval Grey Number Distance Entropy

Information entropy is an important concept in information theory, applied to measure the disorder degree of system. For a specific system, if the system is very random, chaotic and without order, the information entropy of the system will be large. Conversely, if a system is determinate, and obeys some order, the information entropy of the system will be small. Shannon proposed the information entropy equation [14]:

$$H = -\sum_{i=1}^{n} Pi \log_2 Pi, \ (i = 1, 2, \dots, n)$$

Pi denotes the occurrence probability of a random event *i*, and *n* denotes the number of random events.

Be similar to the operation of information entropy, the T-PIGN distance entropy can be defined [15]. To express conveniently, let $a(\otimes) = \otimes_1$, $b(\otimes) = \otimes_2$, where $a^L = a$, $a^* = m$, $a^U = b$, $b^L = c$, $b^* = n$, $b^L = d$. **Definition 2:** $\otimes_1 \in [a,m,b] (0 \prec a \le m \le b)$ and $\otimes_2 \in [c,n,d] (0 \prec c \le n \le d)$ are T-PIGN, let

$$H(D) = \frac{1}{3} \left[\left(-\frac{a}{a+c} \ln \frac{a}{a+c} \right) + \left(-\frac{c}{a+c} \ln \frac{c}{a+c} \right) + \left(-\frac{b}{b+d} \ln \frac{b}{b+d} \right) + \left(-\frac{d}{b+d} \ln \frac{d}{b+d} \right) + \left(-\frac{m}{m+n} \ln \frac{m}{m+n} \right) + \left(-\frac{n}{m+n} \ln \frac{m}{m+n} \right) \right]$$
(1)

be the distance entropy of \otimes_1 and \otimes_2 . The grey distance entropy is not the measure of distance, but the measure of approaching degree between \otimes_1 and \otimes_2 , that is to say the T-PIGN distance entropy can represent the information close degree of two T-PIGN.

Theorem: The closer \otimes_1 and \otimes_2 , the larger grey distance entropy H(D); the farther \otimes_1 and \otimes_2 , the smaller H(D). When $\otimes_1 = \otimes_2 (a = c, m = n, b = d)$, H(D) is the maximum;. Proof:

Let

$$H(d_1) = \left(-\frac{a}{a+c}\ln\frac{a}{a+c}\right) + \left(-\frac{c}{a+c}\ln\frac{c}{a+c}\right),$$
$$H(d_2) = \left(-\frac{b}{b+d}\ln\frac{b}{b+d}\right) + \left(-\frac{d}{b+d}\ln\frac{d}{b+d}\right),$$
$$H(d_3) = \left(-\frac{m}{m+n}\ln\frac{m}{m+n}\right) + \left(-\frac{n}{m+n}\ln\frac{n}{m+n}\right)$$
$$\frac{a}{a+c} = P_1, (0 \prec P_1 \prec 1),$$

Thus, we can obtain that: $H(d_1) = -P_1 \ln P_1 - (1 - P_1) \ln (1 - P_1)$.

The derivation of $H(d_1)$ is that: $H(d_1)' = -\ln P_1 - 1 + \ln(1 - P_1) + 1$.

Let $H(d_1)' = 0$, we can get that: $P_1 = \frac{1}{2}$.

Because $H(d_1)'' = -\frac{1}{P_1} - \frac{1}{1 - P_1} \prec 0$, when $P_1 = \frac{a}{a + c} = \frac{1}{2}$, a = c, $H(d_1)$ is the maximum, and

 $\max H(d_1) = \ln 2 \; .$

Similarly, when b = d, $H(d_2)$ is the maximum; when m = n, $H(d_3)$ is the maximum. Therefore, when a = c, b = d and m = n, the distance entropy H(D) is the maximum.

$$\max H(D) = \max \frac{1}{3} \Big[H(d_1) + H(d_2) + H(d_3) \Big] = \ln 2$$

In the same way, the theorem that the farther \otimes_1 and \otimes_2 , the smaller H(D) can be proved. Meanwhile, the properties of grey distance entropy can be got:

1) It has the nonnegative, that is $H(D) \ge 0$. Omit the process of proof;

2) It has the extremum, that is $H(D) \le \ln 2$. The proof process is similar to theorem;

3) It has the symmetry, that is $H(D)_{\otimes_1 \otimes_2} = H(D)_{\otimes_2 \otimes_1}$.

Proof:

$$\begin{split} H(D)_{\otimes_1\otimes_2} &= \frac{1}{3} \Biggl[\left(-\frac{a}{a+c} \ln \frac{a}{a+c} \right) + \left(-\frac{c}{a+c} \ln \frac{c}{a+c} \right) + \left(-\frac{b}{b+d} \ln \frac{b}{b+d} \right) \\ &+ \left(-\frac{d}{b+d} \ln \frac{d}{b+d} \right) + \left(-\frac{m}{m+n} \ln \frac{m}{m+n} \right) + \left(-\frac{n}{m+n} \ln \frac{n}{m+n} \right) \Biggr] \\ H(D)_{\otimes_2\otimes_1} &= \frac{1}{3} \Biggl[\left(-\frac{c}{c+a} \ln \frac{c}{c+a} \right) + \left(-\frac{a}{c+a} \ln \frac{a}{c+a} \right) + \left(-\frac{d}{d+b} \ln \frac{d}{d+b} \right) \\ &+ \left(-\frac{b}{d+b} \ln \frac{b}{d+b} \right) + \left(-\frac{n}{n+m} \ln \frac{n}{n+m} \right) + \left(-\frac{m}{n+m} \ln \frac{m}{n+m} \right) \Biggr] \end{split}$$

Therefore, we can obtain that $H(D)_{\otimes_1\otimes_2} = H(D)_{\otimes_2\otimes_1}$.

3. Selection Method of Evaluation Indicators with Three-Parameter Interval Grey Number

3.1. Selection Principle of Evaluation Indicators with Three-Parameter Interval Grey Number

Let $A = \{A_1, A_2, \dots, A_r\}$ be the scheme set of three-parameter multi-attribute evaluation problems, and $U = \{U_1, U_2, \dots, U_s\}$ be the index set. The index value is $[x_{ij}^L, x_{ij}^*, x_{ij}^U]$ $(i = 1, 2, \dots, r; j = 1, 2, \dots, s)$. Then the evaluation sample matrix X is given as follows:

$$X = \begin{bmatrix} \begin{bmatrix} x_{11}^{L}, x_{11}^{*}, x_{11}^{U} \end{bmatrix} & \begin{bmatrix} x_{12}^{L}, x_{12}^{*}, x_{12}^{U} \end{bmatrix} & \dots & \begin{bmatrix} x_{1s}^{L}, x_{1s}^{*}, x_{1s}^{U} \end{bmatrix} \\ \begin{bmatrix} x_{21}^{L}, x_{21}^{*}, x_{21}^{U} \end{bmatrix} & \begin{bmatrix} x_{22}^{L}, x_{22}^{*}, x_{22}^{U} \end{bmatrix} & \dots & \begin{bmatrix} x_{2s}^{L}, x_{2s}^{*}, x_{2s}^{U} \end{bmatrix} \\ \vdots & \vdots & \ddots & \vdots \\ \begin{bmatrix} x_{r1}^{L}, x_{r1}^{*}, x_{r1}^{U} \end{bmatrix} & \begin{bmatrix} x_{r2}^{L}, x_{r2}^{*}, x_{r2}^{U} \end{bmatrix} & \dots & \begin{bmatrix} x_{rs}^{L}, x_{rs}^{*}, x_{rs}^{U} \end{bmatrix} \end{bmatrix}.$$

In the multi-attribute evaluation problems, if the difference of index value of the same index in all schemes is small, the impact of the index on the evaluation distinguishing degree is small. Conversely, it shows that the impact of the index on the evaluation distinguishing degree is great. Therefore, considering from this angle, the index that has greater difference degree should be retained. By the definition and theorem of the T-PIGN distance entropy, we know that H(D) is inversely proportion to the approaching degree between \otimes_1 and \otimes_2 . So the difference degree of each index can be represented as the T-PIGN distance entropy. Let D_{ij} represent the difference degree of the index U_j in the scheme A_i and other schemes, D_{ij} is defined as follows:

$$D_{ij} = \sum_{k=1}^{\prime} H(D)_{\otimes_{ij} \otimes_{kj}} \quad (k \neq i)$$
⁽²⁾

And let

$$D_{j} = \sum_{i=1}^{r} D_{ij} = \sum_{i=1}^{r} \sum_{k=1}^{r} H(D)_{\otimes_{ij} \otimes_{kj}} \quad (k \neq i)$$
(3)

Because H(D) has the symmetry and D_i is the result of repeated summation, let

$$\tilde{D}_{j} = \frac{1}{2} D_{j} = \frac{1}{2} \sum_{i=1}^{r} D_{ij} = \frac{1}{2} \sum_{i=1}^{r} \sum_{k=1}^{r} H(D)_{\otimes_{ij} \otimes_{kj}} \quad (k \neq i)$$
(4)

 \tilde{D}_i expresses the sum of grey distance entropy of the index U_i in all schemes.

If the grey distance entropy of the index U_i in all schemes is larger, the impact of the index on the evaluation is smaller; Conversely, if the grey distance entropy of the index U_i in all schemes is smaller, the impact of the index on the evaluation is greater. Therefore, considering from the angle of evaluation, the smaller the grey distance entropy of the index U_i , the greater the difference degree of the index U_i , and the index U_i should be retained in the index selection process. The basic idea of this paper is to find and delete redundant indexes by comparing the grey distance entropy of the indexes, and establish the index system more succinctly and reasonably.

3.2. Selection Judgment Criterion of Evaluation Index System with Three-Parameter Interval Grey Number

Obtain the sum vector of grey distance entropy among the schemes under each index by calculating T-PIGN distance entropy, let sum vector $\tilde{D} = \{\tilde{D}_1, \tilde{D}_2, \dots, \tilde{D}_s\}$, and calculate its variance σ , and sort the index according to the sum of grey distance entropy. If $\tilde{D}_1 \prec \tilde{D}_2 \prec \dots \prec \tilde{D}_s$, we can obtain $U_1 \succ U_2 \succ \dots \succ U_s$. And then remove the index which has the biggest distance grey entropy, the number of original index set decreases from *s* to s-1, the weight of the removed index is assigned to the rest of indexes according to the original index weight proportion.

In the new evaluation sample matrix, because the grey distance entropy sum among the schemes under each

index is constant, calculate the variance of surplus index grey distance entropy directly, and it is denoted as σ' . Compare the relative error between σ and σ' expressed as $\Delta = \frac{|\sigma - \sigma'|}{\sigma}$, if $\Delta \succ \theta$ (θ is the set value, the

greater θ , the greater the selection degree), it shows that rejecting this index has great impact on the whole index system, so this index should not be rejected, index selection is finished, evaluation index system at this time is optimal; if $\Delta \leq \theta$, it shows that rejecting this index has small impact on the whole index system, within the acceptable extent, this index can be rejected, continue the selection of index system. Repeating the above process until the relative error of adjacent variances is greater than the set value θ , index selection can be finished.

4. Example Analysis

Evaluation and selection of cadres is a multi-factors evaluation problem. A unit made 6 assessment index in the cadre assessment and selection: ideology and morality (U_1) , work attitude (U_2) , work style (U_3) , educational level (U_4) , leadership (U_5) and development ability (U_6) . Scoring for the index through the mass discussion (range from 0 to 100), and identifying 5 candidates A_i (i = 1, 2, 3, 4, 5) according to the statistical result. The index value of each candidate is T-PIGN, the index weight is w = (0.172, 0.144, 0.174, 0.078, 0.190, 0.242), data comes from [16], and taking $\theta = 10\%$.

First, establish the evaluation matrix X.

$$X = \begin{bmatrix} 80,85,90 & [90,92,95 & [91,94,95 & [93,96,99 & 90,91,92 & [95,97,99] \\ [90,95,99 & [89,90,93 & [90,92,95 & [90,92,95 & 94,97,98 & [90,93,95] \\ [88,91,95 & [84,86,90 & [91,94,97 & [91,94,96 & 86,89,92 & [91,92,94] \\ [85,87,90 & [91,93,95 & [85,88,90 & [86,89,93 & 87,90,94 & [92,93,96] \\ [86,89,95 & [90,92,95 & [90,95,97 & [91,93,95 & 90,92,96 & [85,87,90] \end{bmatrix}$$

Calculate the grey distance entropy of 5 candidates by using Equation (1), and the result is shown in Table 1. Based on Table 1, we can obtain the results as follows by using Equation (4).

$$\begin{split} \tilde{D}_{1} &= \frac{1}{2} D_{1} = \frac{1}{2} \sum_{i=1}^{5} D_{i1} = \frac{1}{2} \sum_{i=1}^{5} \sum_{k=1}^{5} H(D)_{\otimes_{i1} \otimes_{k1}} = 6.9269 \; ; \\ \tilde{D}_{2} &= \frac{1}{2} D_{2} = \frac{1}{2} \sum_{i=1}^{5} D_{i2} = \frac{1}{2} \sum_{i=1}^{5} \sum_{k=1}^{5} H(D)_{\otimes_{i2} \otimes_{k2}} = 6.9293 \; ; \\ \tilde{D}_{3} &= \frac{1}{2} D_{3} = \frac{1}{2} \sum_{i=1}^{5} D_{i3} = \frac{1}{2} \sum_{i=1}^{5} \sum_{k=1}^{5} H(D)_{\otimes_{i3} \otimes_{k3}} = 6.9292 \; ; \\ \tilde{D}_{4} &= \frac{1}{2} D_{4} = \frac{1}{2} \sum_{i=1}^{5} D_{i4} = \frac{1}{2} \sum_{i=1}^{5} \sum_{k=1}^{5} H(D)_{\otimes_{i4} \otimes_{k4}} = 6.9297 \; ; \\ \tilde{D}_{5} &= \frac{1}{2} D_{5} = \frac{1}{2} \sum_{i=1}^{5} D_{i5} = \frac{1}{2} \sum_{i=1}^{5} \sum_{k=1}^{5} H(D)_{\otimes_{i5} \otimes_{k5}} = 6.9289 \; ; \\ \tilde{D}_{6} &= \frac{1}{2} D_{6} = \frac{1}{2} \sum_{i=1}^{5} D_{i6} = \frac{1}{2} \sum_{i=1}^{5} \sum_{k=1}^{5} H(D)_{\otimes_{i6} \otimes_{k6}} = 6.9278 \; . \end{split}$$

Thus, $\tilde{D} = \{6.9269, 6.9293, 6.9292, 6.9297, 6.9289, 6.9278\}$, and its variance $\sigma = 1.12362 \times 10^{-6}$. According to the theorem of T-PIGN distance entropy, the influence degree sorting of the index for the candidates is $U_1 \succ U_6 \succ U_5 \succ U_3 \succ U_2 \succ U_4$. Reject the index U_4 that has the smallest effect on the whole index system, the weight of remaining indexes is

$$w_1 = 0.187, w_2 = 0.156, w_3 = 0.189, w_5 = 0.206, w_6 = 0.262.$$

Because the sum of grey distance entropy of each index is constant, the distance entropy is $\tilde{D}' = \{6.9269, 6.9293, 6.9292, 6.9289, 6.9278\}$, and its variance is $\sigma' = 1.08973 \times 10^{-6}$, the relative error is

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H	D)	A	A_{2}	$A_{_3}$	$A_{_4}$	A_{5}
U_1		ln 2	0.6917	0.6925	0.6930	0.6927
	$U_{_2}$	ln 2	0.6931	0.6926	0.6931	0.6931
	$U_{_3}$	ln 2	0.6931	0.6931	0.6926	0.6931
$A_{_1}$	$U_{_4}$	ln 2	0.6930	0.6931	0.6925	0.6930
	U_{5}	ln 2	0.6927	0.6930	0.6931	0.6931
	$U_{_6}$	ln 2	0.6929	0.6928	0.6930	0.6918
	$U_{_1}$	0.6917	ln 2	0.6930	0.6923	0.6928
	$U_{_2}$	0.6931	ln 2	0.6929	0.6931	0.6931
4	$U_{_3}$	0.6931	ln 2	0.6931	0.6928	0.6931
A_{2}	$U_{_4}$	0.6930	ln 2	0.6931	0.6930	0.6931
	U_{5}	0.6927	ln 2	0.6923	0.6926	0.6929
	U_{6}	0.6929	ln 2	0.6931	0.6931	0.6927
	$U_{_1}$	0.6925	0.6930	ln 2	0.6929	0.6931
	U_{2}	0.6926	0.6929	ln 2	0.6925	0.6926
	$U_{_3}$	0.6931	0.6931	ln 2	0.6925	0.6931
$A_{_3}$	$U_{_4}$	0.6931	0.6931	ln 2	0.6928	0.6931
	U_{5}	0.6930	0.6923	ln 2	0.6931	0.6929
	$U_{_6}$	0.6928	0.6931	ln 2	0.6931	0.6927
	$U_{_1}$	0.6930	0.6923	0.6929	ln 2	0.6930
	U_{2}	0.6931	0.6931	0.6925	ln 2	0.6931
٨	$U_{_3}$	0.6926	0.6928	0.6925	ln 2	0.6925
$A_{_4}$	$U_{_4}$	0.6925	0.6930	0.6928	ln 2	0.6929
	U_{5}	0.6931	0.6926	0.6931	ln 2	0.6931
	$U_{_6}$	0.6930	0.6931	0.6931	ln 2	0.6925
	$U_{_1}$	0.6927	0.6928	0.6931	0.6930	ln 2
	$U_{_2}$	0.6931	0.6931	0.6926	0.6931	ln 2
Δ	$U_{_3}$	0.6931	0.6931	0.6931	0.6925	ln 2
A_{5}	$U_{_4}$	0.6930	0.6931	0.6931	0.6929	ln 2
	U_{5}	0.6931	0.6929	0.6929	0.6931	ln 2

 $\Delta = \frac{|\sigma - \sigma'|}{\sigma} = 3\% \prec \theta = 10\%$, therefore, continue to select the index system.

According to \tilde{D}' , we can obtain the influence degree sorting of the index for the candidates is $U_1 \succ U_6 \succ U_5 \succ U_3 \succ U_2$. Reject the index U_2 that has the smallest effect on the whole index system, the remaining indexes weight is $w_1 = 0.222$, $w_3 = 0.224$, $w_5 = 0.244$, $w_6 = 0.310$, the distance entropy is $\tilde{D}'' = \{6.9269, 6.9292, 6.9289, 6.9278\}$, its variance is $\sigma'' = 1.10678 \times 10^{-6}$, the relative error is $\Delta' = \frac{|\sigma' - \sigma''|}{\sigma'} = 2\% \prec \theta = 10\%$, continue to select the index system.

According to \tilde{D}'' , we can obtain the influence degree sorting of the index for the candidates is

the index selection is fi-

	Original evaluation	n index system	Optimal evaluation index system		
	Relative closeness	Ranking	Relative closeness	Ranking	
$A_{_{1}}$	0.5848	2	0.5671	2	
A_{2}	0.6975	1	0.7089	1	
$A_{_3}$	0.4871	3	0.5117	3	
$A_{_4}$	0.4528	4	0.4254	4	
A_{5}	0.4087	5	0.3797	5	
The best candidate	A_{2}		$A_{_2}$		

 Table 2. The close degree and ranking of each candidate.

 $U_1 > U_6 > U_5 > U_3$. Reject the index U_3 that has the smallest effect on the whole index system, the remaining indexes weight is $w_1 = 0.285$, $w_5 = 0.315$, $w_6 = 0.400$, the distance entropy is

$$\tilde{D}''' = \{6.9269, 6.9289, 6.9278\}, \text{ its variance is } \sigma''' = 0.98571 \times 10^{-6}, \text{ the relative error is} \\ \Delta'' = \frac{|\sigma'' - \sigma'''|}{\sigma''} = 11\% \succ \theta = 10\%. \text{ It shows that the index } U_3 \text{ should not be reject, and}$$

nished. The optimal evaluation index system is $U = \{U_1, U_3, U_5, U_6\}$.

Sort the 5 candidates in the original evaluation index system and the optimal evaluation index system through the index system selection, and then get the sorting of candidates by calculating the relative closeness. The result is shown in Table 2.

According to Table 2, we can get that the ranking in original evaluation index system and the optimal evaluation index system through the index system selection is the same, and the influence degree of index U_2 and U_4 is small so that they can be rejected. In addition, we also find that the distinguishing degree of relative closeness is significantly increased after selecting the evaluation index. Therefore, this index system selection method can be used to solve the evaluation problem. The index system after processing is not only comprehensive but also compendious.

5. Conclusions

This paper establishes T-PIGN distance entropy model that can be applied to the selection of evaluation index system with T-PIGN. The selection degree is related to the set value θ , the greater θ is, the greater the selection degree will be. According to the different actual situation, whether there is a certain value still needs further study. In this paper, the value of θ is 10%.

In order to further verify the effectiveness and applicability of the index system selection method, this paper applies this method in [17] and [18]. Finally, the optimal evaluation index system has the same result with the original evaluation index system, that is to say the index system selection method is correct.

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