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Diagnosis of key safety risk sources of long-distance water diversion engineering operation based on sub-constraint theory with constant weight

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ABSTRACT

Due to the facts that there are more risks and difficulties in long-distance water diversion engineering operation, a comprehensive evaluation model of sub-constraint based on constant weight is established based on sub-constraint theory. In order to eliminate the individual differences in the experts' weights, analysis on the differences in experts' weights is implemented based on the correlation theory and induced ordered weighted averaging. In this way, the indicator weights are determined, and the safety risk comprehensive evaluation of long-distance water diversion project operation is realized. Meanwhile, the methods of reducing the indicator's contribution are used for diagnosing key risk sources. Finally, the Henan section of the Middle Route Project of South-to-North Water Diversion is taken as an example to verify the validity and applicability of the model.

Keywords: Long-distance water diversion project; Risk assessment; Correlation degree; IOWA; Sub-constraint; Risk source diagnosis

1. Introduction

With the rapid development of population and economy in the modern society, the shortage of water resources has become the key factors that constrain the sustainable development of human society. Therefore, many countries have planned to build long-distance water diversion projects for allocating water resources rationally and alleviating the present imbalance between supply and demand [1,2,14,15]. The long-distance water diversion project is a high-dimensional water allocation system with multiple targets. It involves complex and various engineering structure and broad drainage basin, so many risks and accidents potentially happen. Given this background, it is crucial to properly manage the risks contained in the operation period of long-distance water diversion projects. It is of great significance to identify and analyze the risk factors for the safe operation of long-distance water diversion projects and rationally assess the risk system [3,4,16].

At present, people have already applied various comprehensive evaluation methods and application ranges. Chen et al. [5] used principal component analysis and fuzzy comprehensive evaluation method to assess the quality of different varieties of cherry fruits, and determined the high quality varieties with higher cultivation value; according to Kassim et al.[17], improved analytic hierarchy process along with the improved TOPSIS method was used to assess the green railway construction scheme. Zhang et al. [6] combined the order relationship method and entropy method to assess the safety management ability of the airport; Ismail et al. [18] used the data envelopment analysis model to establish emergency control scheme for assessing and studying sudden water pollution incidents, so as to provide the scientific basis for the optimization of the scheme. Li et al. [7]

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used the factor analysis method to comprehensively assess the development of high-tech industrial parks; Wu et al. [8] conducted evaluation study on the quality of cultivated land in the Pearl River Delta based on GA-BP neural network. However, most of these evaluations only gave the evaluation results. Further analysis on the factors affecting the evaluation results was not done, and the key influencing factors were not determined.

In the thesis, sub-constraint model based on constant weight is established to achieve the comprehensive evaluation of the operational safety risk undermining the long-distance water diversion project. Also, the risk is diagnosed based on the comparative analysis of the evaluation results after the indictors were removed. As a result, the factors having greater adverse impact on engineering operation safety are determined.

2. Process of the comprehensive evaluation model of sub-constraint based on constant weight

First, the raw data of each indicator are standardized, and the method for aggregating the weight information based on the degree of association and induced ordered weighted averaging (IOWA) is used to determine the weight of each risk indicator [19]. The processed data are brought into the evaluation model of sub-constraint based on constant weight. The safety risk of the long-distance water diversion project is comprehensively assessed according to the model and data and the key risk factors are determined according to the degree of change after the indictors are reduced [9]. The process of the comprehensive evaluation model of sub-constraint based on constant weight is shown in Fig. 1.

3. Theoretical basis for evaluation model of sub-constraint

3.1. Worst value and ideal value of the indicator score

It is supposed that there are two vectors in the evaluation system, namely z^α and z^β, and

$$z^\alpha = \left(z_1^\alpha, z_2^\alpha, \cdots, z_m^\alpha\right)^T = (1,1,\ldots,1)^T \tag{1}$$

$$z^\beta = \left(z_1^\beta, z_2^\beta, \cdots, z_m^\beta\right)^T = \left(0,0,\ldots,0\right)^T \tag{2}$$

Here z_i^α refers to the maximum value of the indicator i, namely "1", and z_i^β refers to the minimum value of the indicator i, namely "0". $i = 1,2,\ldots,m$. z^α is called "secondary vector" in risk assessment; and z^β is called "optimal vector" [10].

In the safety risk evaluation model for the operation in the long-distance water diversion project, the value of each indicator ranges between 0 and 1 after standardization, so the maximum value of all indicators in the standardization is 1 and the minimum value, 0. Therefore, z^α and z^β represent the worst and ideal values of risk, respectively [20]. It is supposed that the vector expression of the standardized score of the evaluation is as follows:

$$z = \left(z_1,\ z_2,\ z_3,\ \ldots,\ z_m\right)^T \tag{3}$$

Among them, $z_i (i = 1,2,\ldots,m)$ refers to the score for the i indicator.

Take $y^\alpha \in [0,1]$. The value of y^α represents the degree to which z is close to z^α, and y^α is the secondary degree of membership. Similarly, the following formula can be obtained:

$$z^c = \left(1-z_1, 1-z_2, \cdots, 1-z_m\right)^T \tag{4}$$

Take $y^\beta \in [0,1]$, the value of y^β represents the degree to which z is close to the ideal value of z^β. y^β refers to the optimal degree of membership. For an evaluation object, the larger y^α is, the smaller y^β is. The vector expressions of z and z^c measured by y^α and y^β are complementary, therefore

$$y^\alpha + y^\beta = 1 \tag{5}$$

3.2. Establishment of sub-constraints

The establishment of the sub-constraints requires selecting one indicator to be removed. The kth indicator to be removed is marked as S_k and the score of the indicator z_k is changed to 0 with the scores of other indicators remaining

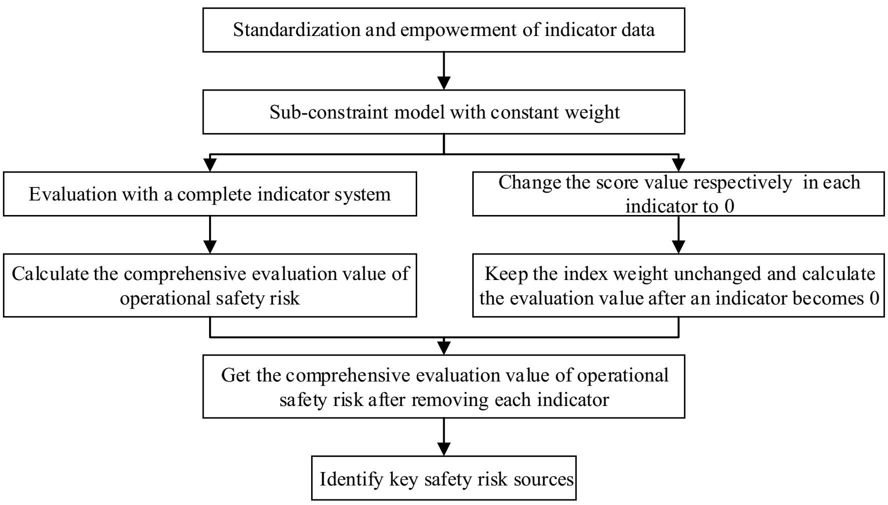

Fig. 1. Process of the comprehensive evaluation model of sub-constraint based on constant weight.

unchanged. The comprehensive score after the *k*th indicator removed is recorded as z^{S_k}.

3.3. Distance between evaluation object score and the worst value

$d(z,z^\alpha)$ is the distance between z and the worst value z^α. In the current research, it is called "secondary specificity". The expression is as follows:

$$d(z,z^\alpha) = \left[\sum_{i=1}^{m} w_i^2 (z_i - z_i^\alpha)^2\right]^{\frac{1}{2}} \tag{6}$$

where z_i is the score of the *i*th indicator, ω_i is the weight of the *i*th indicator, and *m* is the quantity of indicators. Eq. (6) is the weighted average distance between the evaluation object z and the worst value z^α after considering the weight. The closer z is to the worst value z^α, the smaller $d(z,z^\alpha)$ is; the farther z is from the worst value z^α, $d(z,z^\alpha)$ becomes larger.

It is supposed that y^α is the score for the distance $d(z,z^\alpha)$ between z and z^α. The weighted degree of speciality $D(z,z^\alpha)$ is the product of $d(z,z^\alpha)$ and y^α, namely:

$$D\left(z,\ z^\alpha\right) = y^\alpha d\left(z,\ z^\alpha\right) \tag{7}$$

3.4. Distance between evaluation object score and the ideal value

$d(z,z^\beta)$ is the distance between z and the ideal value z^β. In the current research, it is called "excellent degree" with its expression as follows:

$$d(z,z^\beta) = \left[\sum_{i=1}^{m} w_i^2 (z_i - z_i^\beta)^2\right]^{\frac{1}{2}} \tag{8}$$

Eq. (8) is the weighted average distance between the evaluation object z and the ideal value z^β after considering the weight. The closer z is to the ideal value z^β, the smaller $d(z,z^\beta)$; the farther z is away from the ideal value z^β, the greater $d(z,z^\beta)$ is.

It is supposed that y^β is the score of $d(z,z^\beta)$, namely, the distance between z and z^β. It is supposed that the weighted degree of excellence "$D(z,z^\beta)$" is the product of $d(z,z^\beta)$ and y^β, namely:

$$D\left(z,\ z^\beta\right) = y^\beta d\left(z,\ z^\beta\right) \tag{9}$$

4. Standardization and weights

4.1. Standardization of indicator data

4.1.1. Positive indicator [11]

$$z_i = \frac{v_i - v_{\min}}{v_{\max} - v_{\min}} \tag{10}$$

where z_i is the score of the *i*th indicator and v_i is the original value of the *i*th indicator.

4.1.2. Negative indictor

$$z_i = \frac{v_{\max} - v_i}{v_{\max} - v_{\min}} \tag{11}$$

4.1.3. Moderate indicator

$$z_i = \begin{cases} 1 - \dfrac{q - v_i}{\max(q - v_{\min}, v_{\max} - q)}, v_i < q \\ 1 - \dfrac{v_i - q}{\max(q - v_{\min}, v_{\max} - q)}, v_i > q \\ 1 \qquad v_i = q \end{cases} \tag{12}$$

4.2. Indicators' weights based on the relational analysis and IOWA operator

4.2.1. Analysis on the characteristics of weight information

As each expert varies in their different professional experience and different areas of expertise, different experts have different understandings on the importance of the same indicators, which can be called "individual differences" [12]. In the overall distribution, the small individual differences are called "weak differences"; At the same time, the obvious individual differences are called "strong differences". The individual weight information with small differences will be in the "subject position" in the information aggregating process, and the individual weight information with great differences will be in the "secondary position" in the process.

By using the grey relational analysis (GRA), the individual information of different weights of "differences" is analyzed, and the IOWA operator is used to aggregate multiple weight information when the expert's weight is unknown [21].

4.2.2. Measuring the differences of the weight information based on relational analysis

The degree of consistency between the indicator weights provided by the different experts on the application of the relational analysis and the overall expert judgment reflects the "differential" information in order to determine the degree of influence of each individual weight on the final overall weight aggregation [13,22]. The following is the steps of establishing the resolution model for weight information difference based on the degree of association:

Step 1: Set the number of experts to *p*, the expert set to B_t (t = 1,2,...,p), and the weight data set of the expert *t* to the indicator *i* is $R_i = \{r_1, r_2, \ldots, r_p\}$.

Step 2: Solve the overall distribution function of the weight data set. Take $r_1, r_2, \ldots, r_p$ as a set of sample values of the overall data, obey the normal distribution $N(\text{m},\sigma^2)$, and then the maximum likelihood estimator of m and s^2 is:

$$\begin{cases} \hat{\mu} = \dfrac{1}{n}\displaystyle\sum_{t=1}^{p} r_t \\ \sigma^2 = \dfrac{1}{n-1}\displaystyle\sum_{t=1}^{p}\left(r_t - \dfrac{1}{n}\sum_{t=1}^{p} r_t\right) \end{cases} \tag{13}$$

Step 3: Separation of weight data. The literature gives the probability that the sample data fall within different numerical intervals [20]. The sample distribution probability is shown in Fig. 2. The weight data individuals falling within

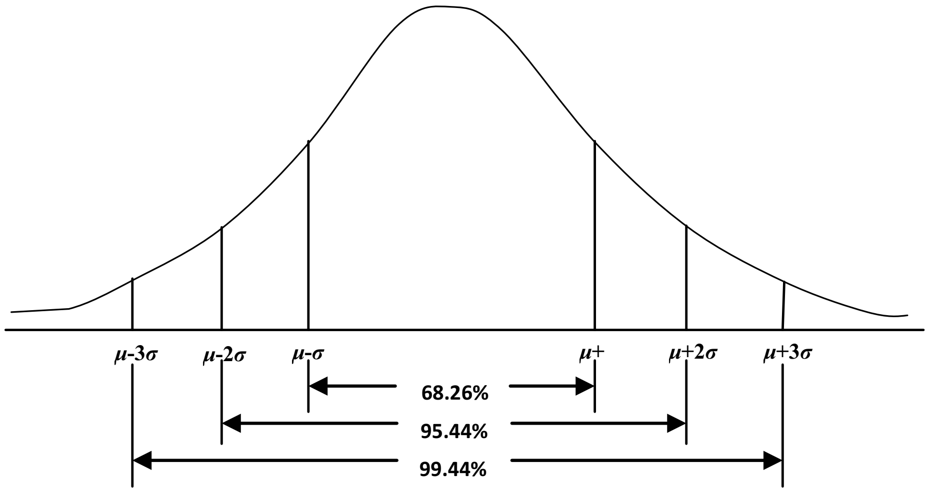

Fig. 2. Sample distribution probability.

the interval of [μ–σ,μ+σ] are referred to as "weak differential data", and those outside the interval are referred to as "strong differential data."

Step 4: Calculate relational degree of ε_t of the weight individual r_t in relation to the overall weight distribution.

- The absolute distance of r_t relative to the mean distribution mean:

$$\Delta_t = \left| r_t - \mu \right|, t = 1,2,\cdots,p \tag{14}$$

- After standardization:

$$\varepsilon_t = \frac{\Delta_t(\min) + \rho\Delta_t(\max)}{\Delta_t + \rho\Delta_t(\max)}, t = 1,2,\cdots,p \tag{15}$$

where Δ_t(min) and Δ_t(max) are the maximum and minimum values of the absolute distance set $\{\Delta_1,\Delta_2,\ldots,\Delta_p\}$, respectively. ρ is the resolution coefficient. In the GRA, the value range is [0.1,0.5]. For the "strong differential" data, when $\Delta_t \notin \left[\mu - \sigma, \mu + \sigma\right]$, ρ = 0.1; For the "weak differential" data, $\Delta_t \in \left[\mu - \sigma, \mu + \sigma\right]$, ρ = 0.5.

- Aggregation of weight information based on IOWA operator
  The OWA operator and the IOWA operator are defined as follows [19]:
  Definition 1: Set the function f: $R^n \to R$, then

$$f_w(a_1, a_2, \cdots, a_n) = \sum_{j=1}^{n} w_j b_j \tag{16}$$

where ω_j is the weight associated with the function f: $\omega_j \in [0,1]$, $\sum_{j=1}^{1} w_j = 1$; As b_j is the jth largest element in $(a_1,a_2,...,a_n)$, the function f_ω is referred as the OWA operator.

Definition 2: Set $<e_1,a_1>,<e_2,a_2>,\ldots,<e_n,a_n>$ as the n two-dimensional arrays, then:

$$f_w(<e_1,a_1>,<e_2,a_2>,\cdots,<e_n,a_n>) = \sum_{j=1}^{n} w_j a_{h(j)} \tag{17}$$

Then the function f_ω is referred as the n-dimensional IOWA operator generated by $e_1,e_2,\ldots,e_n$. In concrete, e_j is the induced value of a_j. $h(j)$ is the subscript of the jth largest number after e_j is sorted in descending order; $W = (\omega_1,\omega_2,\ldots,\omega_n)^T$ is the OWA weight vector. ω_1 is independent of the magnitude of the induction of a_j. Instead, it is related to the location of the a_j induction value [23]. The specific steps are as follows:

- According to the OWA operator theory, $(a_1,a_2,\ldots,a_n)$ are sorted in descending order. With 0 as the start, it has achieved the result $b_0 \geq b_1 \geq \ldots \geq b_{n-1}$. As the weight ω_j is directly determined by C_{n-1}^j, and $\sum_{j=0}^{n-1} w_{j+1} = 1$, hence:

$$w_{j+1} = \frac{C_{n-1}^j}{\sum_{k=0}^{n-1} C_{n-1}^k}, j = 0,1,\cdots,n-1 \tag{18}$$

Based on $\sum_{k=0}^{n-1} C_{n-1}^k = 2^{n-1}$, there are

$$w_{j+1} = \frac{C_{n-1}^j}{2^{n-1}} \tag{19}$$

- When the weight information is aggregated by the IOWA operator, the individual weight of r_t is a_j. Takes ε_t, which is corresponding to r_t, as the induced value, therefore, the p weight ε_t and weight of r_t form p data pairs $(<\varepsilon_1,r_1>,<\varepsilon_2,r_2>,\ldots,<\varepsilon_p,r_p>)$. Thus, the aggregated results of the weights are only related to the individual weights, rather than each expert's weights.
- Normalize the aggregation of weight information for each indicator, so as to obtain the final weight of the indicator. The result is shown as follows:

$$w_i = \frac{f_w(i)}{\sum_{i=1}^{p} f_w(i)} \tag{20}$$

5. Establishment of the evaluation model of sub-constraint based on constant weight and diagnostic model of the key risk sources

5.1. Evaluation model based on the complete indicators' system

$F(y^\alpha)$ is a function with y^α as an independent variable, hence:

$$F\left(y^\alpha\right)=\left(D\left(z,z^\alpha\right)\right)^2+\left(D\left(z,z^\alpha\right)\right)^2 \tag{21}$$

After combining Eq. (5) with Eq. (7), the result is shown as below:

$$F=\left(y^\alpha d\left(z,z^\alpha\right)\right)^2+\left(\left(1-y^\alpha\right)d\left(z,z^\beta\right)\right)^2 \tag{22}$$

After deriving y^α, the result is $F'(1) = 0$, and $F(1) = 0$, $F > 0$, so F has a minimum value. It can be said that $dF(y^\alpha)/d(y^\alpha) = 0$ has a solution. Solve $dF(y^\alpha)/d(y^\alpha) = 0$, hence:

$$2y^\alpha\left[d\left(z,z^\alpha\right)\right]^2+\left(2y^\alpha-2\right)\left[d\left(z,z^\beta\right)\right]^2=0 \tag{23}$$

As the equation $d(z,z^\beta) \neq 0$, the result is

$$y^\alpha=\frac{1}{1+\left(\dfrac{d(z,z^\alpha)}{d(z,z^\beta)}\right)^2} \tag{24}$$

y^α, hence is the evaluation model without any constraints.

5.2. Evaluation model after changing the score of 1 indicator into 0

As the score of the kth indicator becomes 0, the independent variable changes from y^α to the evaluation score $\left(y^\alpha\right)^{S_k}$, and the function F is marked as F^*.

$$F^*\left(\left(y^\alpha\right)^{S_k}\right)=\left(D\left(z^{S_k},\ z^\alpha\right)\right)^2+\left(D\left(z^{S_k},\ z^\beta\right)\right)^2 \tag{25}$$

$$d(z^{S_k},z^\alpha)=\left[\sum_{i=1}^{m}w_i^2(z_i^{S_k}-z_i^\alpha)^2\right]^{\frac{1}{2}} \tag{26}$$

$$d(z^{S_k},z^\beta)=\left[\sum_{i=1}^{m}w_i^{\,2}(z_i^{S_k}-z_i^\beta)^2\right]^{\frac{1}{2}} \tag{27}$$

As $i = k$, $z_i^{S_k} = 0$; As $i \neq k$, $z_i^{S_k} = z_i$.

As $F^*(0) = 0$, $F^*(0) = 0$, $F^*>0$, it is proven that F^* owns a minimum value. Therefore $dF^*((y^\alpha)^{S_k})/d((y^\alpha)^{S_k}) = 0$ also has a solution, through solving $dF^*((y^\alpha)^{S_k})/d((y^\alpha)^{S_k}) = 0$, the result is as follows:

$$2\left(y^\alpha\right)^{S_k}\left[d\left(z^{S_k},z^\alpha\right)\right]^2+\left(2y^\alpha-2\right)\left[d\left(z,z^\beta\right)\right]^2=0 \tag{28}$$

As $d\left(z^{S_k},z^\beta\right)^2 \neq 0$, the following result can be obtained

$$\left(y^\alpha\right)^{S_k}=\frac{1}{1+\left(\dfrac{d\left(z^{S_k},z^\alpha\right)}{d\left(z^{S_k},z^\beta\right)}\right)^2} \tag{29}$$

$\left(y^\alpha\right)^{S_k}$ is the evaluation model after changing the score of the kth indicator into 0.

5.3. Diagnostic model of the key risk sources

Set $\Delta\left(y^\alpha\right)^{S_k}$ as the variable quantity for the scores y^α and $\left(y^\alpha\right)^{S_k}$ as follows:

$$\Delta\left(y^\alpha\right)^{S_k}=y^\alpha-\left(y^\alpha\right)^{S_k} \tag{30}$$

For one evaluation object, the evaluation score y^α based on the complete indicator system must be greater than or equal to the evaluation score $\left(y^\alpha\right)^{S_k}$, after removing one indicator, namely:

$$\Delta\left(y^\alpha\right)^{S_k}=y^\alpha-\left(y^\alpha\right)^{S_k}\geq 0 \tag{31}$$

The key indicator model is determined as follows:

$$Q=\max\left\{\Delta\left(y^\alpha\right)^{S_k}\right\},k=1,2,\cdots,n \tag{32}$$

6. Case analysis

6.1. Project overview

The main channel of the middle route of the South-to-North Water Diversion Project starts from the Taohe Canal Headwork in Xichuan County, Henan Province, and passes through the four provinces of Henan, Hebei, Beijing and Tianjin, spanning the drainage area of Yangtze River, Huaihe River, Yellow River and Haihe River. The total length reaches 1,431.945 km [24–29].

In this thesis, the author takes the accident risk of the Henan section of the middle route of the South-to-North Water Diversion Project as an example and uses the evaluation model of the sub-constraint based on constant weight to draw key risk factors.

6.2. Indicator weighting

The risk assessment indicator system for crossing engineering accidents is shown in Fig. 3.

This time, 10 experts in relevant fields were invited to weigh the indicators. The weights of the risk indicator experts are shown in Table 1.

The maximum likelihood estimators of μ and σ are obtained from the overall distribution function of the weight data set: μ = 0.0294, σ = 0.01186 and the trend interval [μ–σ,μ+σ] is [0.0176,0.0413]. Since the three weights of 0.0102, 0.0169 and 0.0541 do not belong to the interval, they are "strong differential data". Also, as the other seven weights are within the interval, they are the "weak differential data."

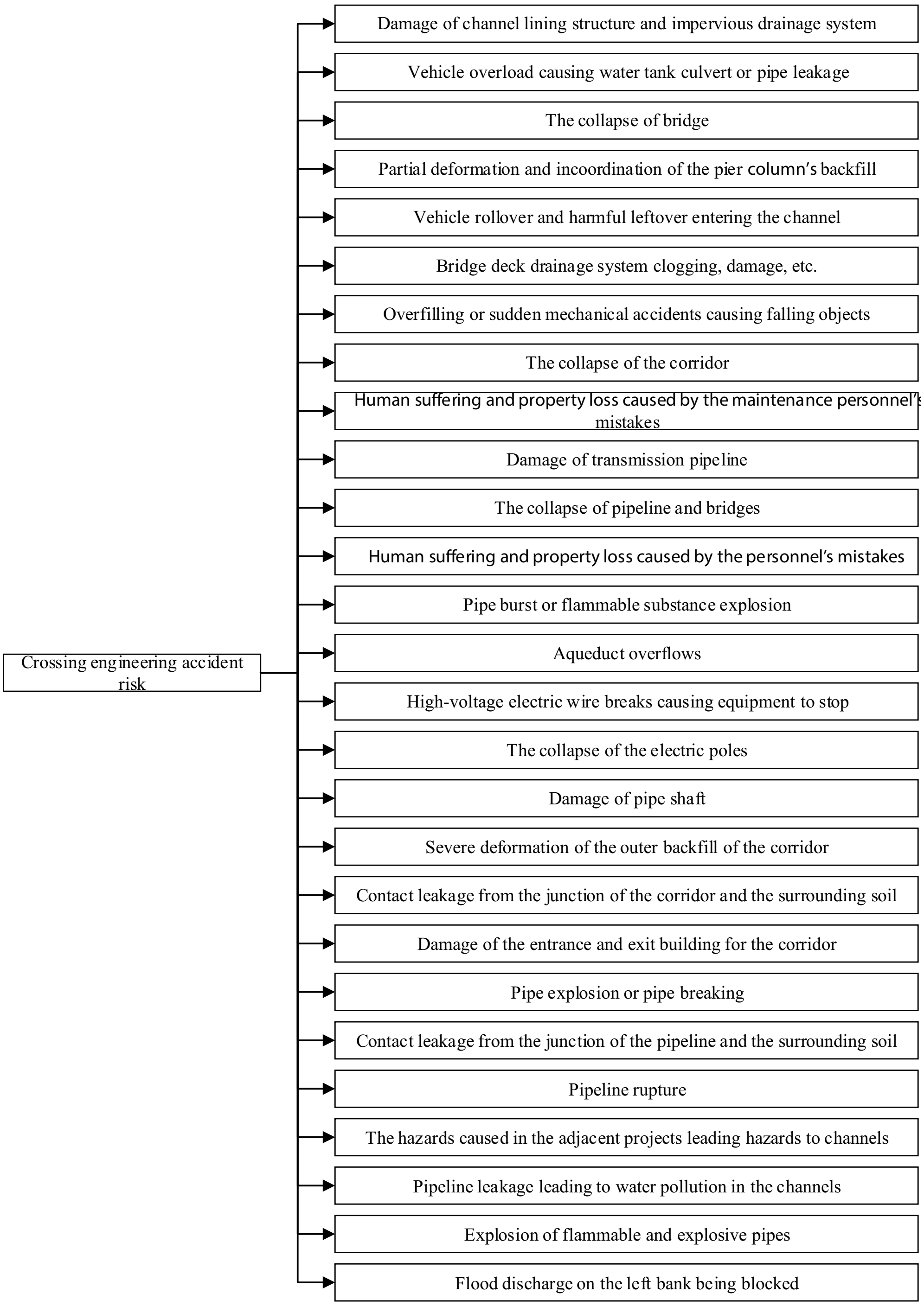

Fig. 3. Risk assessment indicator system for crossing engineering accidents.

The absolute distance set of the individual weight data x_k with respect to the overall distribution value μ are $\{\Delta_1,\Delta_2,\ldots,\Delta_{10}\}$ = {0.0057, 0.0018, 0.0192, 0.0125, 0.0071, 0.0015, 0.0027, 0.0030, 0.0051, 0.0247}, wherein, $\Delta_k(\min)$ = 0.0015, $\Delta_k(\max)$ = 0.0192.

The individual weight data x_k is arranged relatively to the weight distribution ε_k based on the quantity from the largest to smallest, and the sorted correlation degree table is shown in Table 2.

According to the IOWA operator theory, the OWA weight vector W = (0.002, 0.018, 0.070, 0.164, 0.246, 0.246, 0.164, 0.070, 0.018, 0.002) is obtained, and the weight information is further calculated as f_w $(<v_1,a_1>,<v_2,a_2>,\ldots,<v_m,a_m>)$ = 0.0296.

The same procedure may be easily adapted to obtain the aggregation of the weight information for the remaining 26 indicators [30–34]. After the aggregation of indicator weight information being normalized, the weight information

Table 1
Weights of the risk indicator experts

Experts' indicators	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6	Expert 7	Expert 8	Expert 9	Expert 10
d_1	0.0237	0.0312	0.0102	0.0169	0.0365	0.0279	0.0267	0.0324	0.0345	0.0541
d_2	0.0421	0.0374	0.0361	0.0861	0.0198	0.0234	0.0351	0.0465	0.0294	0.0325
d_3	0.1136	0.0413	0.0578	0.0356	0.0236	0.0226	0.0367	0.0654	0.0296	0.0354
d_4	0.0146	0.0566	0.0325	0.0235	0.0266	0.0293	0.0326	0.0364	0.0643	0.0364
d_5	0.0259	0.0202	0.0198	0.0498	0.0346	0.0234	0.0213	0.0459	0.0354	0.0354
d_6	0.0368	0.0621	0.0678	0.0743	0.0672	0.0312	0.0467	0.0354	0.0364	0.0354
d_7	0.0254	0.0421	0.0216	0.0254	0.0354	0.0498	0.0384	0.0249	0.0397	0.0387
d_8	0.1079	0.0123	0.0282	0.0131	0.0551	0.0564	0.0467	0.0321	0.0287	0.0298
d_9	0.0124	0.0356	0.0146	0.0231	0.0433	0.0438	0.0394	0.0316	0.0354	0.0473
d_{10}	0.0325	0.0345	0.0541	0.0254	0.0225	0.0564	0.0344	0.0326	0.0237	0.0354
d_{11}	0.0227	0.0123	0.0196	0.0368	0.0366	0.0298	0.0328	0.0654	0.0321	0.0358
d_{12}	0.0154	0.0482	0.0412	0.0257	0.0374	0.0587	0.0338	0.0347	0.0397	0.0357
d_{13}	0.0114	0.0227	0.0483	0.0247	0.0448	0.0542	0.0347	0.0367	0.0217	0.0368
d_{14}	0.0218	0.0396	0.0237	0.0621	0.0669	0.0548	0.0497	0.0392	0.0328	0.0325
d_{15}	0.0417	0.0598	0.0139	0.0113	0.0222	0.0372	0.0429	0.0287	0.0327	0.0298
d_{16}	0.0301	0.0126	0.0206	0.0471	0.0144	0.0261	0.0321	0.0264	0.0387	0.0542
d_{17}	0.0108	0.0852	0.0609	0.0325	0.0299	0.0325	0.0322	0.0297	0.0387	0.0354
d_{18}	0.0229	0.0191	0.0146	0.0316	0.0387	0.0193	0.0394	0.0394	0.0241	0.0384
d_{19}	0.0634	0.0143	0.0557	0.0361	0.0366	0.0233	0.0354	0.0296	0.0651	0.0384
d_{20}	0.0335	0.0443	0.0698	0.0147	0.0558	0.024	0.0378	0.0354	0.0654	0.0654
d_{21}	0.0341	0.0258	0.0435	0.0225	0.014	0.0237	0.0298	0.0345	0.0634	0.0253
d_{22}	0.0254	0.0497	0.0782	0.0229	0.0433	0.0564	0.0356	0.0322	0.0354	0.0354
d_{23}	0.0365	0.0129	0.0379	0.0563	0.0239	0.0584	0.0264	0.0324	0.0321	0.0247
d_{24}	0.0442	0.0312	0.0215	0.0664	0.0452	0.0348	0.0597	0.0284	0.0241	0.0354
d_{25}	0.0341	0.0635	0.0454	0.0559	0.0124	0.0246	0.0354	0.0345	0.0264	0.0345
d_{26}	0.0425	0.0382	0.0359	0.0247	0.0338	0.0343	0.0398	0.0357	0.0267	0.0364
d_{27}	0.0746	0.0473	0.0266	0.0555	0.0795	0.0437	0.0445	0.0539	0.0438	0.0255

Table 2
Sorted correlation table

ε_6	ε_2	ε_7	ε_8	ε_9	ε_1	ε_5	ε_4	ε_3	ε_{10}
0.0279	0.0312	0.0267	0.0324	0.0345	0.0237	0.0365	0.0169	0.0102	0.0541

aggregation of each indicator has been obtained. The detail is shown in Table 3.

6.3. Evaluation of the worst constraint based on constant weight theory

The degree of risk is quantified and divided into five levels of "1, 3, 5, 7, and 9", which correspond to five levels of "low risk, lower risk, medium risk, higher risk, and high risk". The score "2" indicates a level of risk between lower and low risks. The score "4" represents the level between lower and medium risks. This rule can also be applied to other cases.

The expert scoring method is used to score the risk level in the crossing engineering risk evaluation of the Henan

Table 3
Aggregation of indicator weight information

Indicator	Weight	Indicator	Weight	Indicator	Weight
d_1	0.0317	d_{10}	0.0313	d_{19}	0.0423
d_2	0.0384	d_{11}	0.0344	d_{20}	0.0482
d_3	0.0467	d_{12}	0.0409	d_{21}	0.0284
d_4	0.0301	d_{13}	0.0342	d_{22}	0.0437
d_5	0.0258	d_{14}	0.0427	d_{23}	0.0299
d_6	0.0461	d_{15}	0.0354	d_{24}	0.0349
d_7	0.0353	d_{16}	0.0293	d_{25}	0.0371
d_8	0.0413	d_{17}	0.0355	d_{26}	0.0390
d_9	0.0394	d_{18}	0.0313	d_{27}	0.0465

Table 4
Evaluation table of the crossing engineering risk

No.	Risk indicator	Score	No.	Risk indicator	Score
1	Damage of channel lining structure and impervious drainage system	0.34	15	High-voltage electric wire breaks causing equipment to stop	0.28
2	Vehicle overload causing water tank culvert or pipe leakage	0.28	16	Collapse of the electric poles	0.24
3	Collapse of bridge	0.36	17	Damage of pipe shaft	0.30
4	Partial deformation and incoordination of the pier column's backfill	0.28	18	Severe deformation of the outer backfill of the corridor	0.48
5	Vehicle rollover and harmful leftover entering the channel	0.28	19	Contact leakage from the junction of the corridor and the surrounding soil	0.36
6	Bridge deck drainage system clogging, damage, etc.	0.24	20	Damage of the entrance and exit building for the corridor	0.36
7	Overfilling or sudden mechanical accidents causing falling objects	0.26	21	Pipe explosion or pipe breaking	0.38
8	Collapse of the corridor	0.38	22	Contact leakage from the junction of the pipeline and the surrounding soil	0.40
9	Human suffering and property loss caused by the maintenance personnel's mistakes	0.24	23	Pipeline rupture	0.34
10	Damage of transmission pipeline	0.38	24	Hazards caused in the adjacent projects leading hazards to channels	0.44
11	Collapse of pipeline and bridges	0.34	25	Pipeline leakage leading to water pollution in the channels	0.34
12	Human suffering and property loss caused by the personnel's mistakes	0.32	26	Explosion of flammable and explosive pipes	0.30
13	Pipe burst or flammable substance explosion	0.32	27	Flood discharge on the left bank being blocked	0.44
14	Aqueduct overflows	0.38			

section in the middle route of the South-to-North Water Diversion Project. The experts score according to the analysis of the current project operation and the existing data. As the lower the score of the risk indicator and the smaller the risk, the expert score is treated by the standardization method of negative indicators. After standardization, the table for evaluating crossing engineering risk is shown in Table 4.

Based on the evaluation model without any constraints, $d(z,z^{\alpha}) = 0.1296$, $d(z,z^{\beta}) = 0.0672$ and $y^{\alpha} = 0.2118$.

It can be concluded that the risk assessment score of the crossing engineering of the Henan section of the South-to-North Water Diversion Project is 0.2118, so that it can be said that the risk level is low. The South-to-North Water Diversion Project has many risk factors. Although the safety level of the Zhengzhou section is relatively high, it is still necessary to pay attention to some risky places and factors prone to occur, and prepare for emergency in advance. Furthermore, using sub-constraint based on constant weight is key to assess the key risk items in determining risk factors.

Through changing the score of the first item "damage of channel lining structure and impervious drainage system" into 0, the impact of the risk on the risk score of the water diversion project is removed. At the same time, the weight of the risk is kept unchanged. The result is $\left(y^{\alpha}\right)^{S_k} = 0.2021$.

After ignoring the risk factors for the damage of channel lining structure and impervious drainage system, the risks on the crossing engineering is calculated to be 0.2021. Similarly, after changing the scores of all the risk items into 0 and keeping their weights unchanged, the risk scores of the projects are calculated. By comparing it with the risk score from the evaluation of sub-constraint based on constant weight, the table of the sub-constraint based on constant weight is summarized and shown in Table 5.

Based on $\Delta\left(y^{\alpha}\right)^{S_k}$, it can be concluded that among the risks of crossing engineering projects, after changing the scores of "flood discharge on the left bank being blocked", "contact leakage from the junction of the corrido and the surrounding soil", "contact leakage from the junction of the pipeline and the surrounding soil", "damage of channel lining structure and impervious drainage system" and "aqueduct overflows" into 0, the changes in the final scores of the sub-constraint based on constant weight are greater than the remaining items, so these risks have relatively greater impact on the safety of the project operation. We should focus on them, make emergency plans and conduct drills to reduce the losses caused by the risks. After five evaluation scores of vehicle rollover and harmful leftover entering the channel, the collapse of the electric poles, the collapse of bridge, overfilling or sudden mechanical accidents causing falling objects and the pipeline rupture are reduced to

Table 5
Assessment table on sub-constraint based on constant weight

No.	$\left(y^{\alpha}\right)^{S_k}$	$\Delta\left(y^{\alpha}\right)^{S_k}$	Rank	No.	$\left(y^{\alpha}\right)^{S_k}$	$\Delta\left(y^{\alpha}\right)^{S_k}$	Rank
1	0.1896	0.0222	4	15	0.2024	0.0094	21
2	0.2008	0.0110	15	16	0.2064	0.0054	26
3	0.2049	0.0068	25	17	0.2015	0.0103	18
4	0.2021	0.0097	19	18	0.1967	0.0151	9
5	0.2067	0.0051	27	19	0.1882	0.0236	2
6	0.1988	0.0130	12	20	0.1934	0.0184	7
7	0.2033	0.0085	24	21	0.2027	0.0091	22
8	0.1926	0.0192	6	22	0.1893	0.0225	3
9	0.2022	0.0096	20	23	0.2031	0.0087	23
10	0.2009	0.0109	16	24	0.1952	0.0166	8
11	0.2004	0.0114	14	25	0.1986	0.0132	11
12	0.1970	0.0148	10	26	0.1994	0.0124	13
13	0.2014	0.0114	17	27	0.1830	0.0288	1
14	0.1917	0.0201	5				

zero, the changes in the final scores of the sub-constraint based on constant weight is smaller than the rest items, which indicates that the existing protection of these risks is better and safer, and it is not necessary for paying great attention to them at present.

7. Conclusion

According to the differential weights determined by different experts, the "strong differential" and "weak differential" individual weights are determined by probability theory. Then, the degree of correlations between individual weights and total weight is obtained by using the degree of correlation theory as the inducing factors. The weighted risk factors are determined by the ordered weighted average operator so as to achieve the effective use of each expert weight information. Through the sub-constraint theory, the evaluation model for the operation safety and risks in the long-distance water diversion project is established. Based on all the indicators, the operation safety and risks in the long-distance water diversion project is comprehensively assessed. Then, each indicator's impact is reduced and the weight is kept unchanged. The comprehensive evaluation is carried out again, and the key risk sources are determined according to the magnitude of the changes in the evaluation results, which is conducive to the better management of the risks on the long-distance water diversion project.

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