Health status assessment of scraper conveyor conveying equipment based on cross-entropy theory and immune principle

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Abstract. Based on cross-entropy theory and immunity principle, the paper evaluates the health status of scraper conveying equipment. Firstly, the hierarchical analysis model and immune monitoring model of scraper conveyor equipment are established, and then the cross-entropy theory integrating AHP, fuzzy statistical method and entropy weight method is used to calculate the composite weight of scraper conveyor conveyor equipment index, and finally the health status assessment results are obtained. Combined with the case analysis, the proposed health status assessment method can effectively combine the physical characteristics and operating status of each index of scraper conveying equipment to complete the health status assessment of scraper conveying equipment.

Keywords: Scraper conveying equipment; Health status assessment; Cross-entropy theory; Principles of immunity.

1. Introduction

The paper is supported by the Shandong Province Key R&D Plan (Major Science and Technology Innovation Project) "Research and Application of Key Technologies for Intelligent Mining of Complex Geological Conditions in Working Faces" (project number: 2020CXGC011501), and completed the research by collecting relevant data. As an important underground coal and material transportation equipment, the health status of scraper conveying equipment directly affects the economic benefits of mines, so it is particularly important to establish a suitable health assessment method for this equipment. In order to evaluate the health status of an object, it is necessary to select the relevant algorithm to calculate the weight of the object index, and the commonly used algorithms include AHP[1], fuzzy comprehensive evaluation[2], gray correlation method[3], BP neural network method[4], etc. Literature[5] proposes to combine analytic hierarchy method and fuzzy comprehensive evaluation method to evaluate the construction of new energy projects, but new methods can still be found to improve the accuracy of weight calculation. Literature[6] uses analytic hierarchy method and entropy weight method to calculate the weight coefficient of building curtain wall, but this method has limitations for the problem of redundant mining equipment data collected. Literature[7] for three-phase transformers, a cooperative game method combining three methods is proposed for state of health assessment, which further improves the calculation accuracy by calculating the proportional coefficient of the three weights, but the method does not have computer adaptive ability. Literature[8] uses cross-entropy theory to predict photovoltaic power generation, and improves the accuracy of combined prediction by dynamically changing the weights of different prediction methods. In the paper, by reviewing the data, selecting suitable performance indicators to build a hierarchical analysis model and immune model of scraper conveying equipment, and using the cross-entropy theory fusion of AHP, fuzzy statistical method and entropy weight method to calculate the composite weight of indicators, the accuracy of the final evaluation results is further improved.

2. Health assessment model

2.1 Hierarchical analysis model

In the paper, the key component indicators affecting the healthy operation of scraper conveyor equipment are selected to build a hierarchical analysis model, as shown in Figure 1. The figure divides the scraper conveyor equipment into a two-stage system, the first stage is the component layer and the second stage is the indicator layer.
3. Algorithmic judgment

3.1 Determine weights based on AHP

The AHP is a subjective method of calculating weights, and preliminary estimates of indicator weights are made based on expert experience. According to the hierarchical analysis model established above, the affiliation between the indicators is determined, and the pair-by-two comparison is carried out, and an \( n \)-th order judgment matrix \( A \) is obtained for the importance of \( n \) different indicators of the same level relative to the corresponding components of the previous layer, as follows.

\[
A = (a_{ij})_{n \times n}
\]  

Formula: \( a_{ij} > 0; a_{ij} = 1/a_{ji}; a_{ii} = 1 \). The 1-9 scale method is used to represent the results of pair-by-two comparisons of the importance of different indicators, as shown in Table 1.

<table>
<thead>
<tr>
<th>Scale value</th>
<th>Meaning</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Consistent importance</td>
</tr>
<tr>
<td>3</td>
<td>Slightly more important</td>
</tr>
<tr>
<td>5</td>
<td>Important</td>
</tr>
<tr>
<td>7</td>
<td>Very important</td>
</tr>
<tr>
<td>9</td>
<td>Extremely important</td>
</tr>
<tr>
<td>2, 4, 6, 8</td>
<td>Take the middle value</td>
</tr>
</tbody>
</table>

Calculate the maximum eigenvalue of \( A \) and its corresponding eigenvector, and perform normalization calculations to obtain the initial weight vector as

\[
\vec{W}^{(1)} = [w_1^{(1)}, w_2^{(1)}, ..., w_n^{(1)}]
\]  

Use equations (3) and (4) to test the consistency of the constructed matrix.

\[
CI = \frac{\lambda_{\text{max}} - n}{n - 1}
\]

\[
CR = \frac{CI}{RI}
\]

where \( CR \) is the \( A \) random consistency ratio, \( CI \) is a conformance indicator of \( A \), \( RI \) is the average random consistency index of \( A \), which can eliminate the influence of matrix order. \( \lambda_{\text{max}} \) is the maximum feature value of the judgment matrix, and \( n \) is the total number of indicators. Table 2 lists the values of \( RI \). In general, in the case of \( n \geq 3, \) when \( 0 < CR < 0.10 \), it indicates that each index can be assigned a reasonable weight value. Conversely, the values of the comparison matrix should be readjusted according to Table 2 until the degree of agreement is satisfactory.
3.2 The weights are determined based on the fuzzy statistical method
Fuzzy statistics is an objective method for calculating weights. The health status of scraper conveyor conveying equipment is divided into 5 levels, and the definition evaluation set is \( T_b = \{ T_1, T_2, T_3, T_4, T_5 \} \) = \{“health”, “sub-health”, “mild pathology”, “moderate morbidity”, “severe morbidity”\}. The fuzzy statistical method used here is to let the \( n \) experts participating in the assessment obtain the level of each health index according to the set \( T_b \) given earlier, and then count the frequency of each health indicator \( Q_i \) belonging to each assessment level \( \delta_{ij} \), then the degree of membership of the health assessment index belongs to the health level is

\[
\lambda_i^{(s)} = \frac{\delta_{ij}}{n}
\]

In view of the practical significance of each health index in the evaluation system, two fuzzy distribution forms of benefit type and cost type are considered. Set the value in \((a, b)\), and insert three equinoxes in the interval. Assuming that the actual value of any indicator \( Q_i \) is \( z \), the expression of the two membership degree functions is given.

3.2.1 Benefit type

\[
\lambda_i^{(1)} = \begin{cases} 
1 & z \geq b \\
(z - c_i) / d & c_i \leq z < b \\
0 & z < c_i 
\end{cases}
\]

\[
\lambda_i^{(2)} = \begin{cases} 
(z - c_i) / d & c_i \leq z < c_{s+1} \\
(z_{s+1} - z) / d & c_{s+1} \leq z < c_{s+2} \\
0 & z \geq c_{s+2} 
\end{cases}
\]

\[
\lambda_i^{(3)} = \begin{cases} 
(z - c_i) / d & c_i \leq z < c_{s+1} \\
(z_{s+1} - z) / d & c_{s+1} \leq z < c_{s+2} \\
0 & z \geq c_{s+2} 
\end{cases}
\]

\[
\lambda_i^{(4)} = \begin{cases} 
1 & z \geq c_2 \\
(c_2 - z) / d & a \leq z < c_2 \\
0 & z < a 
\end{cases}
\]

Formula \( a \) is the optimal cut-off value, \( b \) is the optimal cut-off value, \( d = (b-a)/4 \), \( s=2,3,4 \). Let \( a = c_1 \) and \( b = c_5 \).

3.2.2 Cost type

\[
\lambda_i^{(1)} = \begin{cases} 
1 & z < b \\
(c_2 - z) / d & a \leq z < c_2 \\
0 & z \geq c_2 
\end{cases}
\]

3.3 The weights are determined based on the entropy weight method
The entropy weight method is also an objective method for determining weights. The main calculation steps are as follows:

1. Normalize the original data. The system indicators collected by the sensor are normalized to the original data matrix with \( k \) objects, \( l \) evaluation indicators, and the \( i \)-th component and \( j \)-th index

\[
x_{ij}(n) = \frac{x_i(n) - x_{ij}(n)}{x_i(n) - x_j(n)} (i = 1, 2, ..., k; j = 1, 2, ..., l_i)
\]

where \( x_{ij}(n) \) is the \( n \)-th detection value of the \( j \)-th index of the \( i \)-th component, \( x_a \) is the worst value of the indicator,
$x_b$ is the optimal value of the indicator, $x_j(n)$ is the normalized value of $x_j(n)$.

2. The information entropy of the $i$-th object and the $j$-th indicator in the system is

$$E_{ij} = -\alpha \sum_{n=1}^{n} (p_j(n) \ln p_j(n))$$

where $p_j(n) = x_j(k) / \sum_{n=1}^{n} x_j(k)$, $\alpha = 1/\ln n$.

3. Determine the weight. The weight of the $i$-th element and the $j$-th indicator is defined as

$$w_j^{(3)} = \frac{1 - E_{ij}}{l_i - \sum_{j=1}^{l} E_{ij}}$$

Indicator weight vector for the $i$-th object

$$\tilde{w}_i^{(3)} = [w_{i1}^{(3)}, w_{i2}^{(3)}, ..., w_{ij}^{(3)}]$$

### 3.4 Composite weights are determined based on cross-entropy theory

Cross-entropy theory is used to quantify the difference between two probability distributions. In the uniform probability space, cross-entropy is defined for two different distributions $p$ and $q$, as follows: When discrete, $p$ and $q$ are probability vectors, defined as

$$D(p\|q) = \sum_{j=1}^{n} p_j \ln \frac{p_j}{q_j}$$

When continuous, $p$ and $q$ are probability density functions, defined as

$$D(p\|q) = \int_{a}^{b} p(x) \ln \frac{p(x)}{q(x)} dx$$

3.5 Calculate health values

The sensor cell uploads the collected data information to the immune cell and outputs a state sequence vector

$$\tilde{K}_i = [K_1, K_2, ..., K_n]$$

where $n$ is the total number of sensor cells, $K_i(i=1,2,...,n)$ outputs the status monitoring information for each sensor cell, with a value of 0 or 1.

The influence factor of the indicator layer on the component layer is

$$T_iE \tilde{w}_i^{\top}$$

The health value of the component can be obtained as

$$H = 1 - \gamma_{E}$$

where the health value $H \in [0,1]$, the larger $H$, the better the health state of the element. By calculating the health value of each element, the target health status assessment is achieved. Table 3 shows the breakdown of health value and health status.

<table>
<thead>
<tr>
<th>health values</th>
<th>1-0.9600</th>
<th>0.9599-0.9</th>
<th>0.8999-0.8</th>
<th>0.7999-0.6</th>
<th>0.5999-0</th>
</tr>
</thead>
<tbody>
<tr>
<td>health states</td>
<td>Health</td>
<td>Sub-health</td>
<td>Mildly morbid</td>
<td>Moderately morbid</td>
<td>Severely morbid</td>
</tr>
</tbody>
</table>

Cross-entropy quantifies the "distance" between two probabilities, and also quantifies the amount of information required between the source of information from probability $p$ to probability $q$, reflecting the degree of agreement between the two probabilities, with the following theorems and properties.

Theorem: $p$ and $q$ are density functions, then $D(p\|q) \geq 0$.

Properties: $D(p\|q) \geq 0$, equal sign holds: if and only if $p = q$ exists almost everywhere.

In the process of combining weight calculation, cross-entropy theory completes data fusion by calculating the proportion coefficient of each single method weight in the combined weight, and obtains a more accurate and reasonable combination weight.
4. Case analysis

Taking a coal mine underground scraper conveying equipment as an example. The sensor cells were installed separately to collect the data of reducer oil temperature $G_1$, reducer oil level $G_2$, reducer input and output shaft temperature $G_3$, cooling water pressure $G_4$, cooling water flow $G_5$ and motor bearing temperature $G_6$. These six indicators are classified in a fuzzy distribution form, as shown in Table 4. The critical value is based on the equipment factory parameters, historical operation records and historical maintenance records.

By collecting the results of each sensor at a certain time, the initial data of each indicator is shown in Table 4. The critical value is based on the information $\{160,448,131,1,5,59,113\}$.

Construct a pairwise comparison matrix $A$ based on analytic hierarchy.

$$A = \begin{bmatrix} 1 & 1/2 & 3/2 & 1/3 & 1/2 & 1/4 \\ 2 & 1 & 3 & 2/3 & 1 & 1/2 \\ 2/3 & 1 & 3 & 2/9 & 1/3 & 1/6 \\ 3 & 2/3 & 9/2 & 1 & 3/2 & 3/4 \\ 2 & 1 & 3 & 2/3 & 1 & 1/2 \\ 4 & 2 & 6 & 4/3 & 2 & 1 \end{bmatrix}$$

The maximum characteristic value is obtained as $\lambda_{max}=6.0$, so $CI=0$, and the consistency check $CR=0.0.1$ is performed to meet the requirements and subsequent calculations are performed.

1) The feature vector corresponding to $\lambda_{max}$ is found and normalized to obtain the weight vector $W^{(1)}=[0.0789,0.1579,0.0526,0.2368,0.1579,0.3158]$ based on analytic hierarchy.

2) The cost-type fuzzy membership function is used for the index $G_1$, $G_3$, $G_4$ and $G_6$, and the benefit-type fuzzy membership function is used for the index $G_2$ and $G_5$, and the weight vector $W^{(2)}=[0.0789,0.1231,0.1062,0.2313,0.1336,0.3290]$ based on the fuzzy statistical method is obtained according to equations (6)-(16).

3) The second set of data of each index was collected as a reference $G^{(3)}=[G_1,G_2,G_3,G_4,G_5,G_6]=\{161,448,132,1,5,59,114\}$. Firstly, the entropy of each index information $E_j=[E_1,E_2,E_3,E_4,E_5,E_6]=[0.9999,0.9999,0.9997,0.9999,0.9264,0.9999]$ is calculated, and then the weight vector $W^{(3)}=[0.00130,0.00130,0.00130,0.00130,0.00130,0.00130]$ is obtained on the entropy weight method is determined.

4) The calculation process of the scale factor for each single method is as follows

1. Define the fusion method. Let $\omega$ be the combined weight vector after fusing the three methods, $\omega^{(r)}$ is the weight vector of the $r$ method, and $\omega^{(r)}$ is known, the dimensions of $\omega$ and $\omega^{(r)}$ are equal to the number of indicators, that is, 6 dimensions, and the fusion is carried out according to the following formula

$$\omega = \sum_{r=1}^{3} k_r \omega^{(r)}$$  \hspace{1cm} (26)

where $k_r$ is the scale coefficient of each single method and satisfies the following formula.

$$\sum_{r=1}^{3} k_r = 1$$  \hspace{1cm} (27)

2. Define the cross-entropy calculation formula.

$$\sum_{r=1}^{3} \sum_{j=1}^{6} \omega_j \ln (\frac{\omega_j}{\omega_j^{(r)}}) = \sum_{r=1}^{3} (k_r \omega_1^{(r)} + k_r \omega_2^{(r)} + k_r \omega_3^{(r)}) \ln (k_r \omega_1^{(r)} + k_r \omega_2^{(r)} + k_r \omega_3^{(r)}) / (\omega_j^{(r)})$$  \hspace{1cm} (28)

where $\omega_j$ is the weight value of the $j$-th index after fusion, and $\omega_j^{(r)}$ is the weight value of the $j$-th index of the $r$ method.

3. Construct the objective function. Given $\omega^{(r)}$, the independent variables in equation (28) are $k_1$, $k_2$, $k_3$, and from equation (27) we get $k_1=1-k_2-k_3$, so the independent variable is defined as $x=[k_1,k_2]$, find the minimum value of equation (28), and construct the objective function $F(x)$.

$$F(x) = \min \sum_{r=1}^{3} D(\omega || \omega^{(r)})$$  \hspace{1cm} (29)

4. Solving the optimization problem $F(x)$.

① Make a second-order approximation Taylor expansion for $F(x)$.

$$F(x) = F(x_0) + (x-x_0)^T \frac{\partial F}{\partial x} + \frac{1}{2} (x-x_0)^T \frac{\partial^2 F}{\partial x^2} (x-x_0)$$  \hspace{1cm} (30)

where $x_0$ is the initial value of the matrix and $A$ is the Heisen matrix.

② Find the $F(x)$ differential

$$G(x) = \frac{\partial F(x)}{\partial x} + \frac{1}{2} (A-A^T)(x-x_0)$$  \hspace{1cm} (31)

③ Set the initial value $x_0$ and the accuracy threshold $\varepsilon$ so that $H_\varepsilon$ is a second-order identity matrix, $i=0$. 

<table>
<thead>
<tr>
<th>Health indicators</th>
<th>Reducer oil temperature $G_1$</th>
<th>Reducer oil level $G_2$</th>
<th>Reducer input and output shaft temperature $G_3$</th>
<th>Cooling water pressure $G_4$</th>
<th>Cooling water flow $G_5$</th>
<th>Motor bearing temperature $G_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Critical value</td>
<td>$0^\circ C \leq G_1 \leq 200^\circ C$</td>
<td>$0 \leq G_2 \leq 450\text{mm}$</td>
<td>$0^\circ C \leq G_3 \leq 200^\circ C$</td>
<td>$0 \leq G_4 \leq 5\text{MPa}$</td>
<td>$0 \leq G_5 \leq 60\text{L/min}$</td>
<td>$0 \leq G_6 \leq 200^\circ C$</td>
</tr>
<tr>
<td>Distribution form</td>
<td>Cost type</td>
<td>Benefit type</td>
<td>Cost type</td>
<td>Cost type</td>
<td>Benefit type</td>
<td>Cost type</td>
</tr>
</tbody>
</table>

Table 4 Indicator layer parameters

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Health indicators</th>
<th>Reducer oil temperature $G_1$</th>
<th>Reducer oil level $G_2$</th>
<th>Reducer input and output shaft temperature $G_3$</th>
<th>Cooling water pressure $G_4$</th>
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<td>Reducer oil temperature $G_1$</td>
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<td></td>
</tr>
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<td>Distribution form</td>
<td>Cost type</td>
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<td>Cost type</td>
<td>Cost type</td>
<td>Benefit type</td>
<td>Cost type</td>
<td></td>
</tr>
</tbody>
</table>

For the index $G_1$, $G_2$, $G_3$, $G_4$, $G_5$, $G_6$, the critical value is based on the information $\{160,448,131,1,5,59,113\}$. Firstly, the entropy of each index information $E_j=[E_1,E_2,E_3,E_4,E_5,E_6]=[0.9999,0.9999,0.9997,0.9999,0.9264,0.9999]$ is calculated, and then the weight vector $W^{(2)}=[0.0789,0.1231,0.1062,0.2313,0.1336,0.3290]$ based on the fuzzy statistical method is obtained according to equations (6)-(16).
④ Solve the search direction $D_i$.

$$D_i = -H_iG_i$$  (32)

⑤ The direction of each iteration still uses $D_i$, but each iteration needs to do a one-dimensional search in this direction to find the optimal step size $t_i$.

$$t_i = \arg \min_{t \in R} F(x_i + tD_i)$$  (33)

⑥ Solve $x_{i+1}$

$$x_{i+1} = x_i + t_iD_i$$  (34)

⑦ To determine whether to continue the iteration, bring equation (34) into equation (31) to get $G_{i+1}$, if $|| G_{i+1} || < \varepsilon_c$, the iteration ends, otherwise the iteration continues.

⑧ To determine $H_{i+1}$, the formula is as follows

$$z_i = G_{i+1} - G_i$$  (35)

$$\delta_i = x_{i+1} - x_i$$  (36)

$$B_i = \frac{\delta_i}{\delta_i}$$  (37)

$$C_i = \frac{-(H_i z_i)(H_i z_i)^T}{z_i^T H_i z_i}$$  (38)

$$H_{i+1} = H_i + B_i + C_i$$  (39)

Continue the iterative solution so that $i=i+1$ goes to step ④. Combined with the above can obtain the $x$ value at the end of the iteration, that is, the proportional coefficients $k_1, k_2, k_3=1-k_1-k_2$ of each method are obtained, and the combined weight $\omega$ is obtained from equation (26). By calculation $k_1=0.3851$, $k_2=0.4176$, $k_3=1-k_1-k_2=0.1973$, the combined weight $\omega = 0.0628$ was obtained from equation (24), and finally the health value of scraper delivery equipment $H=1-0.0628=0.9372$ was obtained from equation (25).

It can be seen that by random value, the health value of the scraper conveying equipment is 0.9372, which is in a subhealthy state, and the equipment can still operate normally, but according to the immune cell output state sequence, maintenance personnel need to pay attention to the lubricating oil temperature of the reducer. The equipment has been in operation underground for one month since the complete overhaul, and the parts are in good operating condition, which is consistent with the calculation results.

5. Summary

In the paper, the hierarchical analysis model and immune model of the scraper conveying equipment are first constructed, and then the initial weight is obtained by the analytic hierarchy method for the initial data collected, the index membership degree is calculated by the fuzzy statistical method, the initial weight is corrected by the entropy weight method, and finally the three algorithms are fused by cross-entropy theory to calculate the health value of the scraper conveying equipment by combining the immune principle. Taking a coal mine underground scraper conveying equipment as an example, the health status assessment was completed to lay the foundation for the subsequent construction of a health management system.

References


