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.

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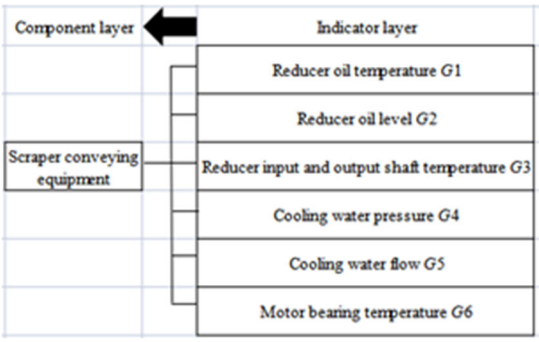

Fig. 1 Hierarchical analysis model

2.2 Immune models

Immunizing a target device goes through three steps: recognition, immunization, and management. Immunological flow diagram shown in Figure 2 and immunity model of scraper delivery device shown in Figure 3.

According to the hierarchical analysis model, the sensor cells corresponding to each index are set up to collect initial data, if the data is within the normal range, it means that there is no antigen, if the data is abnormal, it means that there are abnormal antigens entering the system and the information needs to be transmitted to immune cells. Immune cells are installed at the element layer and are responsible for collecting and aggregating abnormal antigen information for calculation. That is, the cross-entropy theory is used to determine the composite weight, the health value is calculated by the immune principle, the results are uploaded to the management cells, and the backup fault information is updated at the same time. The management cell is equivalent to the data processing terminal computer, which receives the status sequence output by the immune cell and formulates various maintenance measures for failure; Antibodies represent specific repair methods, actuator cells represent maintenance workers, and the goal is to repair individual components to achieve good health.

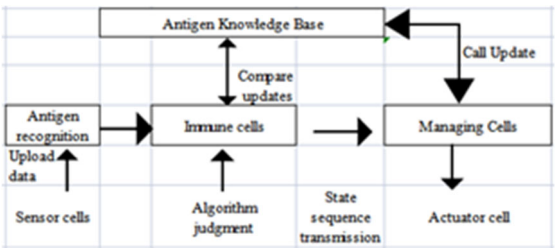

Fig. 2 Immunomonitoring flowchart

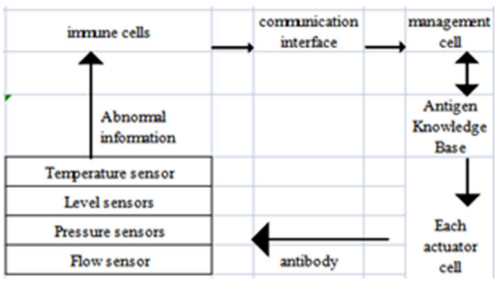

Fig. 3 Immunity model of scraper delivery equipment

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.

$$A = (a_{ij})_{n\times n} \tag{1}$$

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 1. 1-9 proportional scale method

Scale value	Meaning
1	Consistent importance
3	Slightly more important
5	Important
7	Very important
9	Extremely important
2、4、6、8	Take the middle value

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

$$\vec{W}_i^{(1)} = [w_1^{(1)}, w_2^{(1)}, \ldots, w_n^{(1)}] \tag{2}$$

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

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{3}$$

$$CR = \frac{CI}{RI} \tag{4}$$

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. $\lambda_{\max}$ 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 $n \geqslant 3$, 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.

Table 2 Pairs of order 1-9 compare the *RI* values of matrices

n	1	2	3	4	5	6	7	8	9
RI	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45

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_s={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_s given earlier, and then count the frequency of each health indicator Q_i belonging to each assessment level δ_{is}, then the degree of membership of the health assessment index belongs to the health level is

$$\lambda_i^{(s)} = \frac{\delta_{is}}{n} \tag{5}$$

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

$$\lambda_i^{(1)} = \begin{cases} 1 & z \ge b \\ (z - c_4)/d & c_4 \le z < b \\ 0 & z < c_4 \end{cases} \tag{6}$$

$$\lambda_i^{(s)} = \begin{cases} 0 & z \ge c_{5-s+2} \\ (c_{5-s+2} - z)/d & c_{5-s+1} \le z < c_{5-s+2} \\ (z - c_{5-s})/d & c_{5-s} \le z < c_{5-s+1} \\ 0 & z \le c_{5-s} \end{cases} \tag{7}$$

$$\lambda_i^{(5)} = \begin{cases} 0 & z \ge c_2 \\ (c_2 - z)/d & a \le z < c_2 \\ 1 & z < a \end{cases} \tag{8}$$

Formula *a* is the worst critical 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

$$\lambda_i^{(1)} = \begin{cases} 1 & z < b \\ (c_2 - z)/d & a \le z < c_2 \\ 0 & z \ge c_2 \end{cases} \tag{9}$$

$$\lambda_i^{(s)} = \begin{cases} 0 & z < c_{s-1} \\ (z - c_{s-1})/d & c_{s-1} \le z < c_s \\ (c_{s+1} - z)/d & c_s \le z < c_{s+1} \\ 0 & z \ge c_{s+1} \end{cases} \tag{10}$$

$$\lambda_i^{(5)} = \begin{cases} 0 & z < c_4 \\ (c_5 - z)/d & c_4 \le z < a \\ 1 & z \ge a \end{cases} \tag{11}$$

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

According to the degree of affiliation of each health index in the indicator layer to the five health levels, the index evaluation matrix is constructed

$$D_i = [\lambda_i^{(1)} \quad \lambda_i^{(2)} \quad \lambda_i^{(3)} \quad \lambda_i^{(4)} \quad \lambda_i^{(5)}] \tag{12}$$

Sensor cells can output status monitoring information based on membership values. Make

$$e_i = \max\{\lambda_i^{(s)}\} \qquad \text{s=1,2,...,5} \tag{13}$$

When $e_j = \lambda_j^{(4)}$ *or* $e_j = \lambda_j^{(5)}$, the corresponding sensor cell output alarm information is 1. When $e_j = \lambda_j^{(1)}$、$e_j = \lambda_j^{(2)}$ *or* $e_j = \lambda_j^{(3)}$, the sensor cell outputs a normal message of 0. Get the objective correction weights of each indicator

$$\alpha_i = \frac{1/e_i}{\sum 1/e_i} \tag{14}$$

Formula: $\sum 1/e_i$ is the sum of the reciprocals of the e_i values corresponding to all health indicators of a component. Finally, the comprehensive weight of each indicator in the indicator layer is obtained

$$\beta_i = \frac{\alpha_i w_i^{(1)}}{\sum \alpha_i w_i^{(1)}} \tag{15}$$

The indicator layer synthesizes the weight vector

$$\vec{W}_i^{(2)} = [\beta_1^{(2)}, \beta_2^{(2)}, ..., \beta_n^{(2)}] \tag{16}$$

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

$$x_{ij}(n) = \frac{x_a - x_{ij}(n)'}{x_a - x_b}, (i = 1,2,...,k; j = 1,2,...,l_i) \tag{17}$$

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, $x_{ij}(n)$ is the normalized value of $x_{ij}(n)'$.

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

$$E_{ij} = -\alpha \sum_{n=1}^{n} (p_{ij}(n) \mathrm{In} p_{ij}(n)) \tag{18}$$

where $p_{ij}(n) = x_{ij}(k) / \sum_{n=1}^{n} x_{ij}(k)$, α=1/In*n*.

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

$$w_{ij}^{(3)} = \frac{1 - E_{ij}}{l_i - \sum_{j=1}^{l_i} E_{ij}} \tag{19}$$

Indicator weight vector for the *i*-th object

$$\vec{W}_i^{(3)} = [w_{i1}^{(3)}, w_{i2}^{(3)}, ..., w_{il_i}^{(3)}] \tag{20}$$

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

$$D(p\|q) = \sum_{j=1}^{n} p_j \,\mathrm{In} \frac{p_j}{q_j} \tag{21}$$

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

$$D(p\|q) = \int_a^b p(x) \,\mathrm{In} \frac{p(x)}{q(x)} dx \tag{22}$$

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.

3.5 Calculate health values

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

$$\vec{K}_I = [K_1 \quad K_2 \quad ... \quad K_n] \tag{23}$$

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

$$\gamma_E = \vec{K}_I \vec{w}_i^T \tag{24}$$

The health value of the component can be obtained as

$$H = 1 - \gamma_E \tag{25}$$

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 3 The division of health values and health states

health values	1-0.9600	0.9599-0.9	0.8999-0.8	0.7999-06	0.5999-0
health states	Health	Sub-health	Mildly morbid	Moderately morbid	Severely morbid

4. Case analysis

Table 4 Indicator layer parameters

Health indicators	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	motor bearing temperature G_6
Critical value	0℃≤G_1≤200℃	0≤G_2≤450mm	0℃≤G_3≤200℃	0≤G_4≤5MPa	0≤G_5≤60L/min	0≤G_6≤200℃
Distribution form	Cost type	Benfit type	Cost type	Cost type	Benfit type	Cost type

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 $G^{(1)}=\{G_1,G_2,G_3,G_4,G_5,G_6\}=\{160,448,131,1.5,59,113\}$. Construct a pairwise comparison matrix $\boldsymbol{A}$

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

The maximum characteristic value is obtained as λ_{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 λ_{max} is found and normalized to obtain the weight vector $\vec{W}^{(1)}=[0.0789,0.1579,0.0526,0.2368,0.1579,0.3158]$ 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 $\vec{W}^{(2)}=[0.0769,0.1231,0.1062,0.2313,0.1336,0.329]$ 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 $G^{(2)}=\{G_1,G_2,G_3,G_4,G_5,G_6\}=\{161, 448,132,1.5,58,114\}$. 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 $\vec{W}^{(3)}=[0.0013,0.0013,0.0004,0.0013,0.9906,0.0013]$ based 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 $\boldsymbol{\omega}$ be the combined weight vector after fusing the three methods, $\boldsymbol{\omega}^{(r)}$ is the weight vector of the r method, and $\boldsymbol{\omega}^{(r)}$ is known, the dimensions of $\boldsymbol{\omega}$ and $\boldsymbol{\omega}^{(r)}$ are equal to the number of indicators, that is, 6 dimensions, and the fusion is carried out according to the following formula

$$\boldsymbol{\omega}=\sum_{r=1}^{3}k_r\omega^{(r)} \tag{26}$$

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

$$\sum_{r=1}^{3}k_r=1 \tag{27}$$

2. Define the cross-entropy calculation formula.

$$\begin{aligned}\sum_{r=1}^{3}D\left[\omega\middle\|\omega^{(r)}\right]&=\sum_{r=1}^{3}\sum_{j=1}^{6}\omega_j\,\mathrm{In}\left[\omega_j/\omega_j^{(r)}\right]\\&=\sum_{r=1}^{3}\sum_{j=1}^{6}(k_1\omega_j^{(1)}+k_2\omega_j^{(2)}+k_3\omega_j^{(3)})\,\mathrm{In}\left[(k_1\omega_j^{(1)}+k_2\omega_j^{(2)}+k_3\omega_j^{(3)})/\omega_j^{(r)}\right]\end{aligned} \tag{28}$$

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

$$F(x)=\min\left(\sum_{r=1}^{3}D\left[\omega\middle\|\omega^{(r)}\right]\right) \tag{29}$$

4. Solving the optimization problem $F(\boldsymbol{x})$.

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

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

where x_0 is the initial value of the matrix and $\boldsymbol{A}$ is the Heisen matrix.

② Find the $F(\boldsymbol{x})$ differential.

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

③ Set the initial value x_0 and the accuracy threshold ε so that H_0 is a second-order identity matrix, i=0.

④ Solve the search direction D_i.

$$\boldsymbol{D}_i = -\boldsymbol{H}_i \boldsymbol{G}_i \tag{32}$$

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

$$t_i = \arg\min_{t \in R} F(\boldsymbol{x}_i + t\boldsymbol{D}_i) \tag{33}$$

⑥ Solve $\boldsymbol{x}_{i+1}$

$$\boldsymbol{x}_{i+1} = \boldsymbol{x}_i + t_i \boldsymbol{D}_i \tag{34}$$

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

⑧ To determine $\boldsymbol{H}_{i+1}$, the formula is as follows

$$\boldsymbol{z}_i = \boldsymbol{G}_{i+1} - \boldsymbol{G}_i \tag{35}$$

$$\boldsymbol{\delta}_i = \boldsymbol{x}_{i+1} - \boldsymbol{x}_i \tag{36}$$

$$\boldsymbol{B}_i = \frac{\boldsymbol{\delta}_i \boldsymbol{\delta}_i^T}{\boldsymbol{\delta}_i^T \boldsymbol{z}_i} \tag{37}$$

$$\boldsymbol{C}_i = \frac{-(\boldsymbol{H}_i \boldsymbol{z}_i)(\boldsymbol{H}_i \boldsymbol{z}_i)^T}{\boldsymbol{z}_i^T \boldsymbol{H}_i \boldsymbol{z}_i} \tag{38}$$

$$\boldsymbol{H}_{i+1} = \boldsymbol{H}_i + \boldsymbol{B}_i + \boldsymbol{C}_i \tag{39}$$

Continue the iterative solution so that $i=i+1$ goes to step ④. Combined with the above can obtain the $\boldsymbol{x}$ 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 $\boldsymbol{\omega}$ 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 $\vec{W}=[0.0628,0.1122,0.0647,0.1881,0.312,0.2593]$ can be obtained according to equation (26).

5. According to equation (23), the state sequence vector $\vec{K}_I = (1,0,0,0,0,0)$ of the output of each index immune cell was determined, $\gamma_E=0.0628$ 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 sub-healthy 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.

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