Building evaluation system of mining ecological civilization construction based on entropy weight modified AHP hierarchy model

In order to solve the problems in the mining ecological civilization construction with fast update speed, smooth change trend and lack of artificial landmarks, this article proposes an evaluation system of mining ecological civilization construction based on entropy weight modified AHP hierarchy model (EWMAHPHM). This method combines the entropy weight modified AHP hierarchy model and real-time evaluation, firstly establishes the entropy weight modified AHP hierarchy model, then makes entropy weight modification for the predicted residuals, uses the AHP hierarchy model to determine the evaluation indicators of mining ecological civilization construction, and creatively and respectively adopts different entropy weights in the time dimension and space dimension to do weight modification so to have a higher degree of fitness with the reality of social and economic development. The experimental results show that this method can accurately and rapidly evaluate the mining ecological civilization construction in real time and provide reliable confidence assessment, thus have a high practical value.

Keywords: Entropy weight modification, AHP hierarchy model, mining ecological civilization construction, evaluation system.

1. Introduction

The evaluation system of mining ecological civilization is an important part of the construction of mining ecological civilization. The entropy weight modified AHP hierarchy model (EWMAHPHM) has the characteristics as large data volume, high dimensionality, rapid change, etc., and contains a very high potential value, thus has received attention from more and more scholars in recent years[1,2]. The current studies of entropy weight modified AHP hierarchy model (EWMAHPHM) mainly focus on the directions such as sequence segmentation, mode recognition, sequence classification, clustering, etc. Most of them expect to excavate established rules from massive data with time attributes, and often conduct simple elimination treatment for the abnormal points as noises[9,10]. In fact, these small amounts of abnormal data hide important information and are worth further excavation and analysis. The earliest evaluation methods for mining ecological civilization construction use statistics for real-time evaluation, which assumes that the data obeys a certain probability model, and judges the anomaly according to the inconsistency[5,8]. In most cases, the distribution of data is difficult to know in advance, which limits the application scope of this method[4]. The proposed distance-based anomaly evaluation algorithms calculate the distance between all the data in the set, and compare the distance size to determine where the anomaly occurred, but this method is more sensitive to the choice of parameters[6,7]. The many existing evaluation studies of mining ecological civilization construction often aim at the disordered data sets, but do not apply to the orderly correlated entropy weight modified AHP hierarchy model (EWMAHPHM); and, they only consider the anomaly as a kind of dual characteristic, i.e. normal or abnormal, which is inaccurate[3]. In order to meet the needs for evaluation of mining ecological civilization construction, this article proposes a method of building evaluation system of mining ecological civilization construction based on entropy weight modified AHP hierarchy model (EWMAHPHM). By combining the entropy weight modified AHP hierarchy model (EWMAHPHM) with real-time evaluation, it conducts real-time identification of mining ecological civilization construction in the data of entropy weight modified AHP hierarchy model (EWMAHPHM), after identification uses the state transition probability of entropy weight modified AHP hierarchy model (EWMAHPHM), estimates the occurrence probability of the mining ecological civilization construction based on the state change rules of historical data, and realizes the confidence assessment. This method can not only identify the data anomalies in each dimension, but also identify the relationship anomalies between various dimensionalities. In the evaluation process, the model parameters are updated regularly to improve the accuracy of the algorithm. Experimental results show that the method can accurately and quickly conduct a real-time evaluation on the mining ecological civilization construction, give a reliable confidence evaluation, and have a high practical value.

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2. The construction process of the evaluation system of mining ecological civilization construction

2.1. The building of entropy weight modified AHP hierarchy model (EWMAHPHM)

The method of building evaluation system of mining ecological civilization construction based on entropy weight modified AHP hierarchy model (EWMAHPHM) combines the entropy weight modified AHP hierarchy model and real-time evaluation. Firstly, it adopts the predictive thinking to establish the autoregressive model for the data of given entropy weight modified AHP hierarchy model $\{x_1, x_2, ..., x_N, ...\}$, obtains the fitting AHP hierarchy model, makes a posteriori test of the AHP hierarchy model, and identifies the abnormal points in the original sequence. After completion of the evaluation, it uses the state transfer matrix trained by the entropy weight modified AHP hierarchy model to make confidence assessment for the evaluated abnormal points, and finally determines the abnormal situations of the data. The construction process generally includes three phases: (1) model offline training; (2) real-time evaluation of mining ecological civilization construction; (3) model batch update. The specific conditions are as shown in Algorithm 1:

Algorithm 1 building evaluation system of mining ecological civilization construction based on entropy weight modified AHP hierarchy model (EWMAHPHM)

Input: historical data of entropy weight modified AHP hierarchy $\{x_1, x_2, ..., x_N\}$.

Output: each point in the historical data of entropy weight modified AHP hierarchy is normal or abnormal. If abnormal, then simultaneously output the abnormal confidence.

(1) Establish a *p*–order autoregressive model AR(*p*) for historical data, and use the trained model to predict subsequent data values;

(2) Compare the data predicted value obtained in (1) with the actual value to obtain the predicted residuals $\{e_1, e_2, ..., e_N\}$;

3) Calculate the probability density function of the predicted AHP hierarchy model in (2) by use of the kernel density evaluation;

4) With historical data as input, train and establish the entropy weight modified AHP hierarchy model state model, further obtain discrete state sequence $\{C_1, C_2, ..., C_k\}$and state transition probability matrix. The values of the elements in the *i*th line *j*th column of the matrix represent the probability of transition from state C_i to state C_j;

(5) Use the prior probability and conditional probability of the AHP hierarchy model evaluated in (2), calculate the normal and abnormal posterior probability of the new data point x respectively;

(6) Use the logarithm ratio of the posterior probability of the two in (5) as an indicator, determine whether the new data point x is an abnormal point, and the output is normal or abnormal;

(7) For the point where the output is abnormal in (6), use the state transition probability matrix in (4) to calculate the transition probability from the corresponding state of the pre-order data point to the corresponding state of the point, and output the confidence score;

(8) After every N new data arrive and are verified, return to (1), slide the training window backwards for N positions, and update the prediction model; return to (3), update the probability density function; return to (4), input the N data into the entropy weight modified AHP hierarchy model, and update the state transition matrix.

(9) Repeat the above steps until no new data is input.

2.2. Real-time evaluation system of mining ecological civilization construction

The real-time evaluation of mining ecological civilization construction based on entropy weight modified AHP hierarchy model (EWMAHPHM) firstly selects a sliding window with size as L, establishes the p-order autoregressive model of the t moment data x_t and the previous AR(p) historical data $\{C_{t-p},C_{t-p+1}, ..., C_{t-1}\}$ and predicts the moment data value. It calculates the predicted residuals and makes posteriori test based on the entropy weight modification for the predicted residuals so to determine the indicator of the evaluation system of the mining ecological civilization construction in the entropy weight modified AHP hierarchy model. In this process, the corresponding probability calculation is performed by using the kernel density estimation (KDE) that requires no too much prior information.

The entropy weight modified AHP hierarchy model (EWMAHPHM) analyzes and represents the interdependence and correlation between data of entropy weight modified AHP hierarchy model (EWMAHPHM) and is a linear prediction method. Give an entropy weight modified AHP hierarchy model (EWMAHPHM) $\{x_1, x_2, ..., x_t\}$, the p-order autoregressive model AR(p) models the current value tx as a linear combination of its p neighboring historical values plus constant terms and random errors. The EWMAHPHM model is used for data fitting in the first stage of the algorithm.

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In the process of establishing the EWMAHPHM model, the training set can be changed by sliding the training window backward to dynamically update the model. With the trained model predict the data of entropy weight modified AHP hierarchy model (EWMAHPHM), compare the predicted value and the real value of the data, and calculate the predicted residuals:

$$e_t = x_t - \hat{x}_t \tag{1}$$

In the formula, e_t is the predicted residual at the t moment; x_t and $\hat{x}_t$ are the sample value and predicted value for the t moment respectively.

Kernel density estimation (KDE) is a non-parametric evaluation method used to evaluate unknown density functions. Unlike parameter evaluation methods, kernel density evaluation can, under the condition of no prior condition, evaluate the unknown density function according to the data samples, so to achieve the goal of minimum mean square integration error between the estimated and real results.

Kernel density estimation (KDE) obtains a smooth curve by successively placing a moving cell (kernel function) at the position of each data point through superposition. The selection condition of the kernel function is that the function area under a single peak is 1.

Assuming x_1, x_2, ..., x_N are N sample points of the independent identical distribution F, and their probability density is f, then the kernel density function is evaluated as

$$\hat{f}_h(x) = \frac{1}{N}\sum_{i=1}^{N} K_h(x - x_i) = \frac{1}{Nh}\sum_{i=1}^{N} K\left(\frac{x - x_i}{h}\right) \tag{2}$$

In the formula, K(•) is the kernel function, generally satisfying the symmetry and $\int K(x)dx = 1$. The kernel function is a weighting function, in which the distance $(x-x_i)$ from the data point x_i to x affects the size of the weighting effect when the point x_i evaluating the point x. The sample points that are closer to the x point will play a larger weighting effect during the evaluation. The formula is as follows:

$$K(x) = \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}x^2} \tag{3}$$

In formula (2), h(h > 0) is a smooth parameter called bandwidth. The selection of h has a great influence on the evaluation of f(x). When h is very small, only points that are particularly close to x can play a greater role; with the increase of h, the role of the points that are farther from x in the evaluation also increases. The bandwidth h of the standard normal kernel function can be obtained by the Silverman thumb law.

$$h = \left(\frac{4}{3N}\right)^{\frac{1}{5}} \sigma \tag{4}$$

In the formula, σ is the sample standard deviation.

After using the KDE method to obtain the probability density function of the predicted residuals, the residual probability $p(e^t_{t-L})$ at the t moment can be calculated. The specific calculation method is as follows: suppose the AHP hierarchy model obtained after the prediction is $e^t_{t-L} = \{e_{t-L}, e_{t-L+1}, ..., e_t\}$, take the probability of the residual e_i located range interval of any time point i in the time period (t − Lt) as the probability of this point, then

$$p\left(e^t_{t-L}\right) = \prod_{i=t-L}^{t} p\left(e^i\right) \tag{5}$$

After the corresponding probability values are obtained by kernel density estimation (KDE), the EWMAHPHM model is subjected to a posteriori test. A sliding window with a fixed size L' is selected to test whether the current data point and its previous L' data obey the Gaussian distribution $N(0,v_{L'})$ at the same time. If so, it is determined that the data in the window does not have anomalies; on the contrary, anomalies occur. The test hypothesis is as follows:

H_0: at t moment the data has no anomaly and is normal;

H_1: at t moment the data is the abnormal point.

The likelihoods based on the above hypothesis are

$$p\left(e^t_{t-L'} \middle| H_0\right) = \prod_{i=t-L'}^{t} p\left(e^i \middle| v_{L'}\right) \tag{6}$$

$$p\left(e^t_{t-L'} \middle| H_1\right) = \prod_{i=t-L'}^{t} p\left(e_i \middle| v_{L'}\right) \times p\left(e_t \middle| v_{L'}\right) \tag{7}$$

The formula (6) shows the likelihood probability of the data x_t at the t moment being the normal point under the H_0 hypothesis. Since H_0 assumes that there is no data abnormal at the t moment, the variance of the data point at the t moment is the same as the variance $v_{L'}$ of the previous L' data. The formula (7) represents the likelihood probability of the data x_t at the t moment being the abnormal point under the H_1 hypothesis. Here, the variance of the data at the t moment is different from the variance of the previous L' data, and expressed by v_t.

Variance is extremely sensitive in the zero-mean Gaussian probability function. In order to overcome the influence of variance evaluation on the evaluation accuracy of mining ecological civilization construction, the marginal processing method is adopted and the variance is integrated. According to the entropy weight modification formula, the posterior probability of two hypotheses can be obtained respectively

$$p\left(H_0 \middle| e^t_{t-L'}\right) = \frac{p(H_0)}{p\left(e^t_{t-L'}\right)} p\left(e^t_{t-L'} \middle| H_0\right) = \frac{p(H_0)}{p\left(e^t_{t-L'}\right)} \prod_{i=t-L'}^{t} p\left(e_i \middle| v_{L'}\right) =$$
$$\frac{p(H_0)}{p\left(e^t_{t-L'}\right)} \int p\left(e^t_{t-L'} \middle| v_{L'}\right) \times p\left(v_{L'}\right) dv_{L'} \tag{8}$$

$$p\left(H_1 \middle| e^t_{t-L'}\right) = \frac{p(H_1)}{p\left(e^t_{t-L'}\right)} p\left(e^t_{t-L'} \middle| H_1\right) = \frac{p(H_1)}{p\left(e^t_{t-L'}\right)} \prod_{i=t-L'}^{t-1} p\left(e_i \middle| v_{L'}\right) \times p\left(e_t \middle| v_t\right)$$
$$= \frac{p(H_1)}{p\left(e^t_{t-L'}\right)} \int p\left(e^{t-1}_{t-L'} \middle| v_{L'}\right) \times p\left(v_{L'}\right) d\left(v_{L'}\right) \times \int p\left(e_t \middle| v_t\right) \times p\left(v_t\right) dv_t \tag{9}$$

Where, $p(H_0)$ and $p(H_1)$ are respectively the prior probability of the hypothesis H_0 and H_1, satisfying $p(H_0) + p(H_1) = 1$. If the confidence of the mining ecological civilization construction is set to 95%, then $p(H_0) = 0.05$, $p(H_1) = 0.95$. $p(e^t_{t-L'})$ is the prior probability of the fitting residual $e_i (i = t-L', ..., t)$, which is calculated by the residual probability density function obtained by the KDE method.

The formula for calculating the posterior probability after two hypothetical marginalizations is:

$$p\left(H_0 \middle| e^t_{t-L'}\right) = \frac{p(H_0)(2\pi)^{-\frac{L'+1}{2}}\Gamma\left(\frac{L'+1}{2}\right)}{p\left(e^t_{t-L'}\right)A^{-\frac{L'+1}{2}}} \tag{10}$$

$$p\left(H_1 \middle| e^t_{t-L'}\right) = \frac{p(H_1)(2\pi)^{-\frac{L'+1}{2}}\Gamma\left(\frac{L'}{2}\right)\Gamma\left(\frac{1}{2}\right)}{p\left(e^t_{t-L'}\right)A_1^{-\frac{L'}{2}}A_2^{\frac{1}{2}}} \tag{11}$$

$$A = \frac{1}{2}\sum_{i=t-L'}^{t} e_i^2, A_1 = \frac{1}{2}\sum_{i=t-L'}^{t-1} e_i^2, A_2 = \frac{1}{2}e_i^2 \tag{12}$$

In the formula, $\Gamma(\bullet)$ is the gamma function, which is calculated by the following approximate equation:

$$\Gamma(a) \approx \sqrt{2\pi a}\,(a/e)^a \tag{13}$$

In the formula, $\Gamma\left(\frac{1}{2}\right) = \sqrt{\pi}$

The formulas (10) and (11) respectively represent, when the residual is $e^t_{t-L'}$ the probability of the data x_t at the t moment having no anomaly and having an anomaly. Further, the logarithmic ratio $\varphi(t)$ of the indicator posterior probability (shortened as the posterior probability ratio) is introduced to measure the size relationship between the test hypothesis H_0 and H_1, also taken as a basis for the determination of mining ecological civilization construction. The formula is as follows:

$$\varphi(t) = \frac{lg\left[p\left(H_1 \middle| e^t_{t-L'}\right)\right]}{lg\left[p\left(H_0 \middle| e^t_{t-L'}\right)\right]} \tag{14}$$

From formula (14), we can see that if x_t is abnormal, the posterior probability $p(H_1|e^t_{t-L'})$ of the abnormal hypothesis H_1 is much larger than the posterior probability $p(H_0|e^t_{t-L'})$ of the normal hypothesis H_0, $\varphi(t) < 1$, otherwise, it is the opposite. Setting the evaluation threshold of the posterior probability logarithm ratio $\varphi(t)$ to be η, according to the following formula conduct mining ecological civilization construction test for the data sequence:

$$\varphi(t)\begin{cases} \leq \eta, x_t \text{ is abnormal point} \\ = else, x_t \text{ is not abnormal point} \end{cases} \tag{15}$$

In the formula, the evaluation threshold η value is generally around 1, usually taking 0.95.

2.3. Assessment of the setting confidence of the evaluation system of mining ecological civilization construction

After recognizing the mining ecological civilization construction through the entropy weight modified AHP hierarchy model (EWMAHPHM), because the lack of true label for data being truly abnormal, it is also necessary to evaluate and identify the confidence of the abnormal point so to determine how large the probability of the evaluated mining ecological civilization construction being truly abnormal and reduce misjudgments in industrial processes. In this stage, the entropy weight modified AHP hierarchy model (EWMAHPHM) state model and state transition probability matrix are used to determine the probability of transition from the previous data state to the corresponding state of the abnormal point, calculate the possibility of this point having anomaly, and further determine the confidence in the establishment of mining ecological civilization construction hypothesis.

EWMAHPHM conducts unsupervised learning clustering of data, and adopts the “competitive learning” approach in training. Each neuron in the output layer matches the input mode through competition, and finally, only one neuron becomes the winner of the competition. The winning neuron represents the classification of input modes. Since the training samples of the unsupervised learning do not contain expected output or any prior knowledge, EWMAHPHM is suitable for clustering analysis for the data with large data volume and no class labels.

It is assumed that the state vector represented by the output neuron i of the EWMAHPHM model is m_i, after the training sample x is provided to the network, the Euclidean distance between the sample and each state vector, that is, the similarity between the sample and the state vector is calculated; then, the network adjusts the output neuron state vector according to the similarity so to promote the maximum distance between adjacent but dissimilar neurons. At the end of training, the output layer can make the best description for the data distribution of the input samples. The neuron corresponding state vector m_i is updated as follows

$$m_i(t+1) = m_i(t) + h_{C(x),i}\left(x(t) - m_i(t)\right) \tag{16}$$

In the formula, t is the learning step length; x(t) is the training sample of x in t^{th} step, $h_{C(x),i}$ is a decreasing neighbor function. The first subscript C = C(x)is defined as follows:

$$\forall i, \left\|x(t) - m_c(t)\right\| \leq \left\|x(t) - m_i(t)\right\| \tag{17}$$

In the formula, $m_c(t)$ is the neuron most similar to the input sample x(t) in all the neuron state vectors of the t^{th} step, which is called the best matching unit. The decreasing neighbor function in formula (16) usually uses a Gaussian function, which looks like:

$$h_{C(x),i} = a(t)exp\left(-\frac{\left\|r_i - r_c\right\|^2}{2\sigma^2(t)}\right) \tag{18}$$

In the formula, $0 < a(t) < 1$ is a monotonically decreasing learning coefficient; r_i and r_c are the positions of the neuron, $\sigma(t)$ is the width of the neighbor function.

After the EWMAHPHM state model training is completed, a state transition matrix between a state sequence $\{C_1, C_2, ..., C_k\}$ and an output layer neuron can be obtained. The element value $p_{i,j}$ of the i^{th} line j^{th} row in the matrix represents the probability of transition from state C_i to state C_j. Assume that a certain entropy weight modified AHP hierarchy model (EWMAHPHM) $\{x_t, x_{t+1}\}$ is converted to the corresponding state sequence$\{C_i, C_j\}$ by EWMAHPHM. Since x_{t+1} appears after x_t, it can be considered that there has been a transition from state C_i to state C_j, and the transition probability is defined as

$$p_{i,j} = \frac{\text{The time number of the transition from state } C_i \text{ to state } C_j}{\text{The time number of the transition from state } C_i \text{ to all states}} \quad (19)$$

In the above state transition probability matrix, the diagonal elements (state unchanged) take the largest value, the elements close to the diagonal of the transition probability matrix (only transition between neighboring states) have the second largest value, and the peripheral elements of the matrix have the smallest values. Since the maximum transition probability of the stationary data sequence is only about 0.6, while the probability of its neighboring state transition has a significant decrease, and some even fall to about 0.1, the differences of transition probability between different states are not significant.

Assuming x_t to be the mining ecological civilization construction for evaluation, the previous data point is x_{t-1}, that the corresponding states obtained through the trained EWMAHPHM are respectively C_t and C_{t-1}. By querying the state transition probability matrix find out the probability $P_{t-1,t}$ and $P_{t-1,l}$ of transition from state C_{t-1} to state C_t and to the most possible transition state C_l so to obtain the abnormal scoring function:

$$s = 1 - \frac{p\left(\text{state } C_{t-1} \text{ transition to state } C_t\right)}{p\left(\text{state } C_{t-1} \text{ transition to state } C_t\right)} = 1 - \frac{p_{t-1,t}}{p_{t-1,t}} \quad (20)$$

It can be seen from the above formula that the greater the possibility of x_t as mining ecological civilization construction is, the smaller is the probability $P_{t-1,t}$ of transition from the previous data state to the x_t corresponding state, but $P_{t-1,l}$ is a fixed value, which leads to a smaller ratio and an increase in the score s of the abnormal scoring function. The size of the scoring function s represents the probability of occurrence of data anomalies. By calculating this function, we can obtain the abnormal confidence of the evaluated abnormal points during the evaluation process of the entropy weight modified AHP hierarchy model (EWMAHPHM), and output the corresponding anomaly score.

3. Experiment analysis

In order to verify the validity of the evaluation of mining ecological civilization construction and confidence assessment algorithm proposed in this article, we select the artificial data sets and evaluation data sets of mining ecological civilization construction for experimentation, and compare the evaluation results of the algorithm with results of the algorithm of evaluation of mining ecological civilization construction based on the AHP hierarchy model and algorithm of evaluation of mining ecological civilization construction based on residual posterior test. We adopt the following two evaluation indicators to compare the known true anomalies in the artificial data sets and the confirmed anomalies after a screening of the evaluation data sets of the mining ecological civilization construction, and analyze the evaluation effect of the algorithm on mining ecological civilization construction.

$$\text{Accuracy rate} = \frac{\text{Number of the detected true abnormal values}}{\text{Total number of the sample true abnormal values}} \times 100\% \quad (21)$$

$$\text{Recall rate} = \frac{\text{Number of the detected true abnormal values}}{\text{Total number of the sample true abnormal values}} \times 100\% \quad (22)$$

Using the Gaussian function, 500 sets of white noise signals with a mean variance of 1 are randomly generated and 6 abnormal points are added, as shown in Fig. 1.

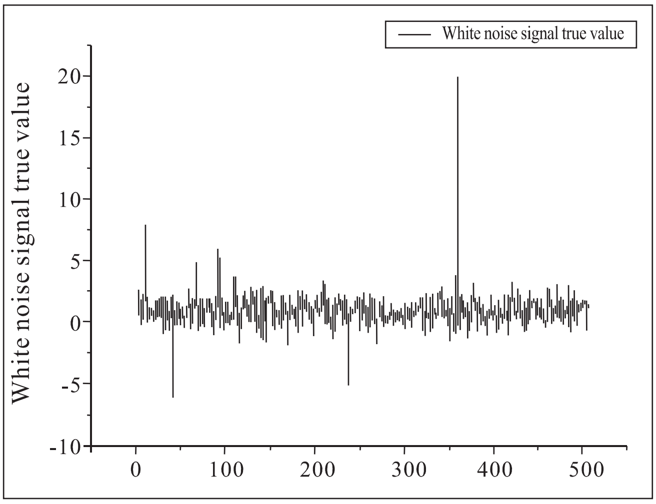

Fig.1: Artificial data set

Using the method of building evaluation system of mining ecological civilization construction based on entropy weight modified AHP hierarchy model (EWMAHPHM) conduct experiments, set the parameters as sliding window size L = 90 and posterior probability ratio test threshold $\eta = 0.8$, and get the posterior probability ratio of this white noise data as shown in Fig.2.

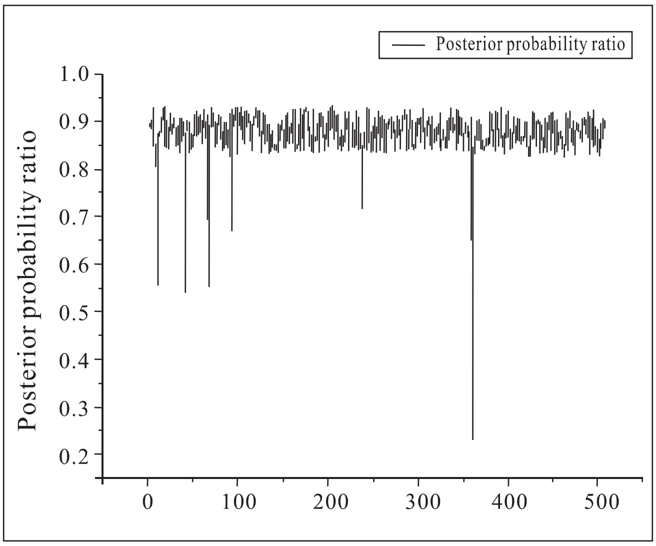

Fig. 2: Artificial data set posterior ratio

As can be seen from Fig. 2, the posterior probability ratio at the abnormal point is significantly smaller than the non-abnormal point. With the setting of the evaluation threshold φ = 0.82, all inserted abnormal points can be evaluated. Further, we perform EWMAHPHM modelling to obtain the state model transition probability matrix and solve the scores for inserted abnormal points. That is, the probability of anomalies is 92%, 90%, 83%, 81%, 78%, and 100%, respectively. On the artificial data sets use the algorithm of evaluation of mining ecological civilization construction based on the AHP hierarchy model and algorithm of evaluation of mining ecological civilization construction based on a residual posterior test for evaluation. Compare the algorithm of this article and obtain results as shown in Table 1. From Table 1, we can see that on the artificial data sets, the algorithm of this article has no misdetection and missed detection, and has high accuracy.

As can be seen from Fig. 3, only the probability ratio of the entropy weight modified AHP hierarchy model (EWMAHPHM) with two significant mutations is lower than the threshold 0.8, and the query shows that there are two data points: 2016/6/304:02 and 2016/6/3012:06, which are consistent with the results of artificial screening.

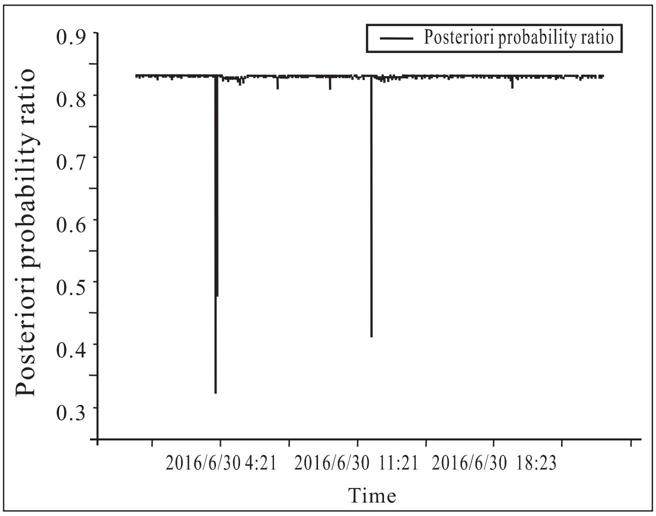

Fig.3: Posteriori probability ratio of smoke emission concentration data

This article compares the proposed method with the algorithm of evaluation of mining ecological civilization construction based on the AHP hierarchy model and algorithm of evaluation of mining ecological civilization construction based on a residual posterior test for evaluation, and obtains the results as shown in Table 2. From Table 2, we can see that the algorithm proposed in this article shows better effects than other algorithms no matter for the artificial data sets or smoke emission concentration data sets. This shows that this method has excellent processing ability and real-time evaluation performance for the industrial entropy weight modified AHP hierarchy model (EWMAHPHM) with large data volume, fast update, and slow change.

TABLE 1. COMPARISON OF RESULTS OF DIFFERENT ALGORITHMS FOR MANUAL DATA SETS

Evaluation algorithm	Number of mining ecological civilization constructions	Number of evaluated mining ecological civilization constructions	Number of misdetections	Number of missed detections
Evaluation of mining ecological civilization construction based on entropy weight modified AHP hierarchy model (EWMAHPHM)	6	0	0	0
Evaluation of mining ecological civilization construction based on the AHP hierarchy model	6	12	6	0
Evaluation of mining ecological civilization construction based on residual posterior test	6	7	1	0

Table 2. Comparison of results of different algorithms for smoke emission concentration data sets

Evaluation algorithm	Number of mining ecological civilization constructions	Number of evaluated mining ecological civilization constructions	Number of misdetections	Number of missed detections
Evaluation of mining ecological civilization construction based on entropy weight modified AHP hierarchy model (EWMAHPHM)	2	2	0	0
Evaluation of mining ecological civilization construction based on the AHP hierarchy model	2	5	3	0
Evaluation of mining ecological civilization construction based on residual posterior test	2	3	1	0

To sum up, the algorithm of evaluation of mining ecological civilization construction can effectively conduct a real-time quick evaluation for mining ecological civilization construction, and have high accuracy.

4. Conclusions

For the evaluation system of mining ecological civilization construction, the speed of updating and slowing down of speed are the major problems facing the construction of the evaluation system. This article proposes a method of building evaluation system of mining ecological civilization construction based on entropy weight modified AHP hierarchy model (EWMAHPHM). This method combines the entropy weight modified AHP hierarchy model (EWMAHPHM) with real-time evaluation. It uses the entropy weight modified AHP hierarchy model (EWMAHPHM) to evaluate the reliability of mining ecological civilization construction, estimates the possibility of occurrence of mining ecological civilization construction according to the law of historical data state changes, and realizes the confidence evaluation. The experimental results show that this method can accurately and quickly conduct a real-time evaluation for the mining ecological civilization construction, also give a reliable confidence assessment, thus have a high practical value.

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