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A multivariate matrix model of analysing mine water bursting and its application

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ABSTRACT

Identifying mine water bursting sources accurately and quickly is the important condition of controlling mine water disasters. In the paper, seven hydrochemistry indexes: Mg^{2+}, Ca^{2+}, $Na^+ + K^+$, HCO_3^-, SO_4^{2-}, Cl^- and TDS were regarded as the evaluation indexes for identifying mine water bursting sources, combined with the importance of hydrochemistry index to water source's identification. Then, ternary mixture model was established based on 28 groups of water sample data collected in the Xinzhuangzi Coal Mine. Furthermore, to test the model's reliability, the model was used to identify the water bursting sources of six groups of water samples in Xuchang Coal Mine under the similar hydrogeological conditions in Xinzhuangzi Coal Mine. The results show that multivariate matrix model for identifying mine water-gushing sources is reliable and practical. Moreover, it can be applied to the actual engineering as well.

Keywords: BP; Water chemistry; DDA; GA-SVM; Coal mine

1. Introduction

Water disaster is one of the mostly encountered five catastrophes in coal mining production. Since 2010, there have been 80 accidents regarding water bursting, water resistant and water irruption happened in Chinese mine sites, of which 9 accidents happened in noncoal mine sites, leading to more than 450 deaths. Therefore, the issue of water bursting has already become a key problem in restricting the efficient development of mine sites [1]. The premise of tacking the water consequences in mines is identifying the water bursting source accurately. Until now, many methods that are used to identify the water bursting source include water chemistry analysis, the particle tracking method, the power spectral method and the isotope tracer technique [2–4]. The mine water is composed of atmospheric rainfall, ice and snow melting and permeating of ground water. Analysing and studying the chemical features and distribution law of the underground water is beneficial to better understanding the existence, supplement, flowing and discharging conditions of underground water. Its nature feature and components are related to the surrounding environment and supplement water sources, which is beneficial to identifying the water bursting origin and further predicting the water disasters. As shown in the water in the Zibo mine site, in the mine water, Ca^{2+} and Mg^{2+} come from calcite and chlorite, while HCO_3^- and SO_4^{2-} come from ground water. As for Na^+ and Cl^-, they come from the coastal rainfall and ancient seawater. Field practices demonstrate that water chemistry analysis is efficient, reliable and economic in identifying the water sources. It mainly uses several quantitative methods, establishing evaluation model based on the water chemistry characteristics. For example, Tong Fengjian was the pioneer who used the water chemistry

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method to successfully identify the water bursting source and bursting channels in Shandong Shengjian Coal Mine, providing the fundamental basement for the following work in addressing the water disasters [5]. Zhang collected six types of water chemistry factors and established a mine water identifying model, based on the hydrogeological conditions in the Jiaozuo Mine [6]. Liu used the genetic algorithm-support vector machine model to identify the water bursting origin in the Maluping Mine and acquired successful results, based on 11 water chemistry factors. Furthermore, there are other effective methods, such as the topology method, the digital different analyser approach, the principal component analysis (PCA) method and the Bayes method. The results acquired based on those methods were acceptable [7–12]. Based on this, in this paper, the authors used the multivariate matrix model to identify the water bursting sources in a mine site, calculate the percentage and different water sources and provide guidance for preventing water catastrophes.

2. The mechanism of the multivariate matrix model

The essence of the multivariate matrix model is multiple linear equations. Based on matrix equations, the unknown numbers can be solved according to the existed coefficients. Therefore, firstly, the matrix equations regarding the unknown numbers should be established. Then, based on the measured data and matrix solving method, the unknown numbers can be solved. Due to the reality that the coal seam is buried in the deep level, during the mining process, the mine water bursting sources are mainly underground strata water. The multivariate matrix model used to identify the water bursting sources considers that the water bursting degree is regarded as unknown numbers. Based on measured data, the extent which the water sample belongs to several water sources can be solved. The multivariate matrix model used in this paper can be depicted as follows:

$$\boldsymbol{QX} = \boldsymbol{S}, \boldsymbol{Q} = \begin{bmatrix} Q_{11} & Q_{12} & \cdots & Q_{1n} \\ Q_{21} & Q_{22} & \cdots & Q_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ Q_{m-1,1} & Q_{m-1,2} & \cdots & Q_{m-1,n} \\ 1 & 1 & 1 & 1 \end{bmatrix}, \tag{1}$$

$$\boldsymbol{S} = \begin{bmatrix} S_1 \\ S_2 \\ \vdots \\ S_{m-1} \\ 1 \end{bmatrix}, \boldsymbol{X} = \begin{bmatrix} P_1 \\ P_2 \\ \vdots \\ P_{n-1} \\ P_n \end{bmatrix} \tag{2}$$

where matrix Q is the standard matrix which is the different water bursting sources' water chemistry indexes; matrix S is the water bursting samples' water chemistry indexes; matrix X is the belonging matrix of water bursting samples which belong to water bursting sources; Q_{ij} ($i = 1, 2, \ldots, m-1$; $j = 1, 2, \ldots, n$) indicates the standard values that different water chemistry indexes exist in different water bursting sources; $m-1$ represents the number of water chemistry indexes; n is the water bursting source; S_i indicates the measured data of water chemistry indexes in water bursting samples; P_i ($i = 1, 2, \ldots, n$) is the extent that water samples which remain to be addressed belong to several water bursting sources. Therefore, it is the unknown numbers that remain to be solved. The maximum P_i in absolute values of P_1, P_2, …, P_n can indicate one water source type and that water source is just the water bursting source which needs to be solved.

3. Collection of mine water sources and water-chemistry indexes

As mining depth increases gradually, the relationship between underground water and ground water together with the water existing in the unconsolidated formation becomes loose. The main water bursting source is underground strata water. Few of them are ground water, atmospheric rainfall and water existing in the unconsolidated formation. Due to the reality that the mine geological conditions are always affected by different factors, even the water chemistry components of same underground water existing in the same mine site can be different [13–19]. This is mainly resulted by the different supplement and discharging conditions in different hydrographic environments. Taking the measured limestone sample data in the Xinzhuangzi Mine Site as an example, the hydrographic environments of underground water in different depths are different. In the same level, the concentration of Na^+ and K^+ decreases with the mining depth increasing. By contrast, the concentration of Ca^{2+} decreases with mining depth increasing. As for the other water chemistry indexes, the values fluctuated and there was no apparent law, which is shown in Fig. 1.

Therefore, in order to improve the accuracy of identifying water bursting sources, the water chemistry indexes and water sample data that are scientific and typical should be selected and studied [20].

Due to the reality that most of the coal seam in the northern China is formed in the Permo-Carboniferous period, the water bursting sources in many mines are similar. They are

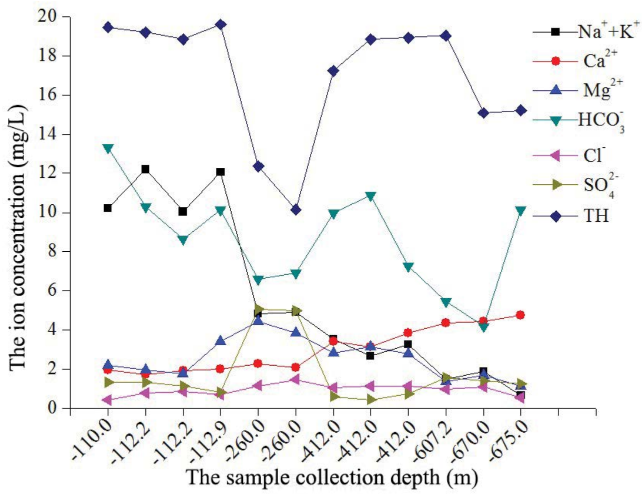

Fig. 1. Relationship between the concentration of water ions in limestone and mining depth.

mainly classified as three types, namely coal seam water (HCO_3-Na·K), limestone water (HCO_3-Ca·Mg, HCO_3-Na and HCO_3-Ca) and Ordovician water (HCO_3-Ca·Mg, HCO_3-Na·Mg and HCO_3-Na·Ca), which are depicted as A, B and C. When the water bursting channels, for example faults, mining discontinuities and detrimental holes, make the mining stope be connected with the water sources, water bursting is extremely likely to occur. Therefore, based on the water chemistry features of the water in the mining stope, the water bursting source location can be predicted beforehand, which is beneficial to arranging alarms and further preventing water disasters from occurring [21]. Selecting the water chemistry factors which are representative and can be easily measured is significant to distinguishing the water source. The Ca^{2+} in underground water usually comes from melting of the sulphate minerals which contain calcium, for example plaster and hard plaster. It is the main component in deciding the hardness of the water, and its content ranges from several milligrams to hundreds of milligram per litre. It is important to distinguishing different water sources. Mg^{2+} also has similar effect. It comes from the resolving of some minerals in dolomite, marlstone and ultrabasic rocks, for example biotite, olivine and homblende. The $Na^+ + K^+$ which is widely distributed in underground water mainly exists with chloride ion in the NaCl water [22]. The Cl^- in underground water mainly comes from the sediment of the rock salt deposit or chloride. It may also come from some minerals of igneous rocks, such as weathering products, like $Ca_5(PO_4)_3Cl$ and $NaAlSiO_4$·NaC. The HCO_3^- in underground water mainly comes from carbonate rocks, for example limestone, dolomite and marlstone [23]. It can easily react with hydroxyl and hydrion, as shown in Eq. (3). The SO_4^{2-} in underground water mainly comes from plaster $CaSO_4 \cdot 2H_2O$ and other deposit sediment. It can also come from native sulphur and sulphide minerals, such as pyrite. The total amount of anion, cation, microelement and compound existing in water is regarded as the degree of mineralisation. The degree of mineralisation has a close relationship with the chemical components of water, as tabulated in Table 1. Considering the effectiveness and significance, seven ions, namely Mg^{2+}, Ca^{2+}, $Na^+ + K^+$, HCO_3^-, SO_4^{2-} and Cl^-, were selected as the distinguishing indexes in the water bursting model. They were represented by the characters K_1, K_2, K_3, K_4, K_5, K_6 and K_7.

$$\begin{cases} HCO_3^- + H^+ = H_2O + CO_2 \\ HCO_3^- + OH^- = H_2O + CO_3^{2-} \end{cases} \tag{3}$$

Table 1
Classification of mineralisation degree in water

Type	Total degree of mineralisation (g/L)
Freshwater	<1
Brackish water	1~3
Saline water	3~10
Salt brine	10~50
Brine	>50

4. Model establishing

The geologic condition in Huainan Coal Mine is typical in northern China. From 1947 when the coal was constructed, the Xinzhuangzi Mine conducted a quantity of experiments on pumping and discharging water as well as water bursting, accumulating a vast number of geologic references. The water bursting source is mainly the water in joints in the main roof or coal seam water, the water in Ordovician limestone or Ordovician limestone water and the water in joints in rocks belonging to Carboniferous period or limestone water. Regarding the documents provided by the geologic measuring department of the mine as the test sample, the authors established the multivariate matrix model which is used to distinguish the water sources. In different places, the authors collected 33 groups of data, in which 28 groups were regarded as the training samples, while the left 5 groups were regarded as the test samples. The analysis results of water chemistry features are tabulated in Tables 2 and 3.

Based on the water sample data, the corresponding piper chart can be drawn, as shown in Fig. 2. According to Fig. 2, it can be known that the difference of water quality in different aquifers is small. Furthermore, there is a phenomenon of cross distribution. Therefore, the water type in the sandstone is HCO_3-Na·K. As for the types of limestone water and Ordovician limestone water, they belong to HCO_3-Ca·Mg. Based on the mechanism of the multivariate matrix model, this model is a triplet model. Selecting the accurate water chemistry parameters as the intermediate factors is quite significant to solving the problems. Restricted by the mining area, the water bursting's degree of mineralisation changed marginally. Therefore, the degree of mineralisation can be regarded as the intermediate parameter for the model. After that, a second ion factor which has a linear relationship with the degree of mineralisation can be selected to acquire three unknown factors, namely P_1, P_2 and P_3. Based on the fitting of the sample data, there is a strong relationship between K_3, K_4 and K_7 and the corresponding correlation indexes are 0.9713 and 0.9320. The fitting curves are shown in Figs. 3 and 4. In this calculating process, the three indexes were mutually solved. The degree of mineralisation which has the maximum value is regarded as the standard value, as shown in Table 4.

When $Na^+ + K^+$, HCO_3^- and TDS are regarded as solvable variables respectively, the formulas are shown below:

$$\begin{cases} K_{7A}P_1 + K_{7B}P_2 + K_{7C}P_3 = K_7 \\ K_{3A}P_1 + K_{3B}P_2 + K_{3C}P_3 = K_3 \\ P_1 + P_2 + P_3 = 1 \end{cases} \tag{4}$$

$$\begin{cases} K_{7A}P_1 + K_{7B}P_2 + K_{7C}P_3 = K_7 \\ K_{4A}P_1 + K_{4B}P_2 + K_{4C}P_3 = K_4 \\ P_1 + P_2 + P_3 = 1 \end{cases} \tag{5}$$

where the front two equations represent the result acquired by multiplying the average value of one specific water source factor by the degree of membership. The characters behind the equal sign represent the laboratory values of the water sample that waits for testing. The water source which has the maximum P_i is just the water source that needs to be tested. Due to the reality that chemical reaction can happen

Table 2
The water chemistry analysis of training samples

Number	Factors (mg/L)							Type
	Mg^{2+}	Ca^{2+}	$Na^+ + K^+$	HCO_3^-	SO_4^{2-}	Cl^-	TDS	
1	4.61	1.34	237.95	533.90	25.53	12.14	548.52	*A*
2	4.41	2.00	339.79	620.57	54.59	125.95	837.20	*A*
3	3.81	2.19	235.42	443.62	49.28	66.88	579.39	*A*
4	3.81	2.31	342.78	812.8	29.42	10.70	795.42	*A*
5	4.81	3.04	333.67	761.53	28.71	5.97	757.0	*A*
6	5.81	4.50	339.71	647.39	46.44	123.89	844.05	*A*
7	2.40	0.61	277.61	652.88	15.60	16.87	639.53	*A*
8	4.41	3.92	327.29	819.46	23.04	5.35	773.74	*A*
9	2.00	1.22	352.13	755.53	14.54	12.35	760.01	*A*
10	2.00	2.07	298.77	698.98	13.47	10.29	674.09	*A*
11	71.54	29.43	41.40	386.87	29.42	29.64	394.87	*B*
12	91.58	26.27	16.10	379.54	28.71	19.14	371.57	*B*
13	79.96	27.97	17.94	356.97	29.07	19.14	352.57	*B*
14	85.77	26.14	21.16	407.0	29.42	36.84	402.83	*B*
15	89.98	24.07	10.81	358.17	25.53	16.88	346.36	*B*
16	86.37	25.89	24.15	386.85	25.17	20.99	376.00	*B*
17	88.38	24.07	31.05	389.9	27.85	27.37	393.67	*B*
18	94.19	29.54	19.32	370.37	34.39	44.86	407.49	*B*
19	89.58	24.31	14.26	356.34	26.59	23.87	356.78	*B*
20	90.58	24.56	19.78	369.13	26.59	28.81	374.89	*B*
21	91.78	24.68	11.04	356.34	27.65	22.64	355.96	*C*
22	58.72	24.93	28.52	331.93	19.50	8.05	305.69	*C*
23	61.32	18.60	24.84	210.52	41.12	50.83	301.97	*C*
24	97.39	29.43	27.14	330.12	40.41	91.58	451.01	*C*
25	79.36	23.59	23.00	284.35	38.99	54.54	361.66	*C*
26	52.30	29.30	22.08	223.32	98.29	59.68	313.31	*C*
27	90.18	27.23	13.57	345.36	34.39	33.75	371.80	*C*
28	48.70	33.51	28.05	354.51	22.34	6.17	318.03	*C*

Table 3
Water chemistry analysing results of training samples

Number	Factors (mg/L)							Type	Analysis
	Mg^{2+}	Ca^{2+}	$Na^+ + K^+$	HCO_3^-	SO_4^{2-}	Cl^-	TDS		
1	5.21	2.55	373.36	422.26	61.33	357.17	1,010.75	*A*	*A*
2	4.81	2.07	469.00	743.22	56.37	281.74	1,182.60	*A*	*A*
3	92.79	28.58	24.61	10.81	358.17	25.53	16.88	*B*	*B*
4	88.38	22.85	31.51	361.83	34.03	37.04	747.06	*B*	*B*
5	58.10	23.10	29.44	238.24	46.08	59.27	424.63	*C*	*C*

among ions, the calculated P_i can be negative. Therefore, the authors define that the absolute degree of membership which is the largest represents the water bursting source of this mine. In order to confirm the credibility of the approach used in this paper, the training samples are used as the confirming data. The $Na^+ + K^+$ and TDS are used as variables and solved with Eq. (3). The factors of P_1, P_2 and P_3 are solved one by one. The maximum P_i just represents the water bursting source in this mine, and the calculating results are shown in Table 3. According to the results, the analysing results of six training samples are quite consistent with the reality, indicating that the approach used in this paper has high credibility. Therefore, it can be used as an effective approach to distinguish the water bursting source and provides a new approach to examine the water bursting source [24].

5. Engineering practices

The Xuchang Coal Mine belonging to the Shandong Energy Zibo Mine Group was constructed in 1999. The maximum

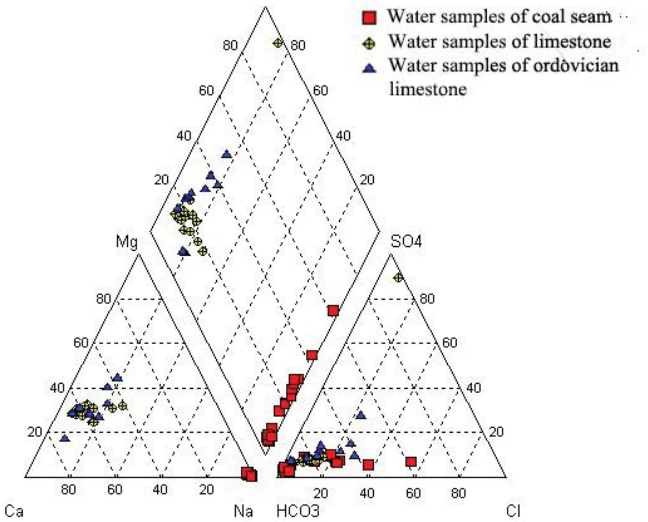

Fig. 2. The piper chart of the water chemistry characteristic of underground water in Xinzhuangzi Mine.

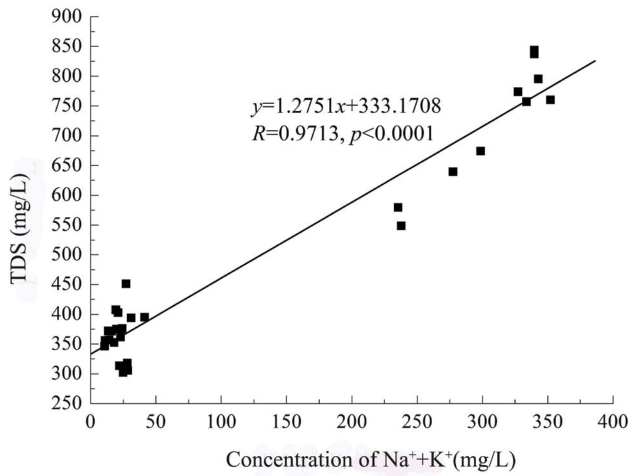

Fig. 3. Linear relationship between $Na^+ + K^+$ and TDS.

output ability is 3.2 million tons. It mainly mines three coal seams, namely 3_{down}, 16_{up} and 17. The coal seam was formed in the Permo-Carboniferous period. The immediate roof is composed of different types of limestone. The floor of the coal seam 17 was composed of Ordovician limestone. Based on the investigating documents, the mine site was threatened by water occurring in aquifers, for example cement–lime, lime and Ordovician limestone. The water disaster was always the problem that restricted the mine development. Based on comparison of the geologic conditions, this mine's geologic condition was quite similar to that in Xinzhuangzi Mine. Furthermore, the water bursting sources were also the same. Therefore, the constructed multivariate matrix model could be applied on the Xuchang Coal Mine. Firstly, it can be used to check the credibility of the approach used in this paper. In addition to that, it can provide guidance for preventing the water bursting disasters. Based on the geologic references provided by this mine's technology department, the authors collected 6 groups of water samples in the levels of –265 m (labelled 1–4) and –500 m (labelled 5–6). Then, water chemistry analysis was conducted on those samples [25]. The water chemistry components and water sources are tabulated in Table 5.

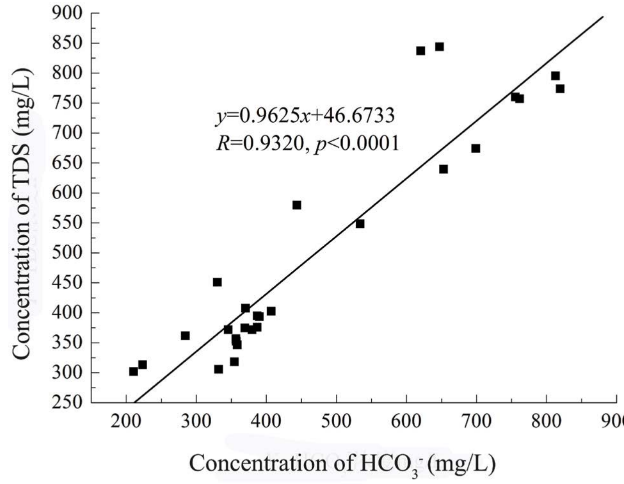

Fig. 4. Linear relationship between HCO_3^- and TDS.

Table 4
The standard values of the water chemistry factors

Water source	K_3 (mg/L)	K_4 (mg/L)	K_7 (mg/L)
A	339.71	647.39	844.05
B	19.32	370.37	407.49
C	27.14	330.12	451.01

Table 5
Water chemistry analysis of water samples collected in the Xuchang Coal Mine

Number	Factors (mg/L)							Type
	Mg^{2+}	Ca^{2+}	$Na^+ + K^+$	HCO_3^-	SO_4^{2-}	Cl^-	TDS	
1	7.41	3.16	346.69	674.24	53.18	121.83	869.39	*A*
2	88.78	26.62	12.42	357.76	26.94	25.93	359.47	*B*
3	85.77	28.57	17.48	363.66	28.72	30.05	372.42	*B*
4	82.96	28.93	25.99	366.10	28.22	40.34	389.49	*B*
5	101.2	31.62	17.01	381.97	48.22	36.84	425.88	*C*
6	84.97	12.04	11.96	251.31	37.74	24.69	297.06	*C*

Table 6
Analysis results of the water bursting sources in the Xuchang Coal Mine

Number	Type 1			Results	Type 2			Results	BP	PCA	SVM
	P_1	P_2	P_3		P_1	P_2	P_3				
1	1.01	–0.49	0.48	*A*	1.07	0.08	–0.16	*A*	*A*	*A*	*A*
2	0.01	2.17	–1.18	*B*	–0.08	1.35	–0.26	*B*	*B*	*B*	*B*
3	0.02	1.97	–0.99	*B*	–0.06	1.29	–0.22	*B*	*B*	*B*	*B*
4	0.04	1.78	–0.82	*B*	–0.03	1.14	–0.11	*B*	*B*	*B*	*B*
5	–0.02	0.37	0.66	*C*	0.04	0.01	0.96	*C*	*B*	*C*	*C*
6	0.05	–3.06	4.00	*C*	–0.32	0.60	0.72	*C*	*C*	*B*	*C*

According to the water chemistry analysis of 6 groups of water samples, the distinguishing results are shown in Table 6. In order to further check the credibility of the approach, the error back propagation (BP) network, PCA and the approach of support vector machine (SVM) were used to distinguish the water samples from the Xuchang Coal Mine. The results are tabulated in Table 6. From Table 5, it can be known that in the multivariate matrix model, TDS, $Na^+ + K^+$ and HCO_3^- were used as intermediate variables and the calculating results were consistent. The predicted results were exactly the same as the reality. Compared with the BP network and PCA, this method was more accurate. Therefore, it is reasonable to apply the multivariate matrix model in the mine water bursting scenario. Furthermore, this model can be expanded in engineering practices. Also, as the mining depth was going deeper and deeper, the mine was rigorously threatened by the Ordovician limestone water. The mine should use six different approaches, namely investigating the water, exploring the water location, discharging the water, releasing the water pressure, blocking the water and stopping the water, to prevent the water disaster consequences.

6. Conclusions

Distinguishing the water bursting sources accurately plays a significant role in preventing the mine water disasters and realising using water resource to explore minerals. In this paper, the multivariate matrix model was used to distinguish the water bursting sources. The main conclusions include

- The piper chart was drawn based on the training samples which were related to geologic conditions of the Xinzhuangzi Mine. The types of water bursting sources were analysed, and the multivariate matrix model was constructed.
- The geologic condition of Xuchang Coal Mine was quite similar to that of Xinzhuangzi Coal Mine. In this paper, the authors applied the multivariate matrix model in distinguishing the water bursting sources. The results showed that this model's accuracy was 100% and it was credible. With mining depth increasing, the bursting water in mines is mainly Ordovician limestone water. Therefore, the mine is gradually threatened by the limestone water. Furthermore, mining companies should especially pay attention to preventing water catastrophes.
- It should be mentioned that the water chemistry components were complex. There are many different indexes, such as pH, hardness, oxygen consumption, free CO_2, NO_3^-, NO_2^-, NH_4^+, F^-, Br^- and I^-. From now on, more work should be conducted on finding indexes that are related to water sources. Increasing the number of distinguishing indexes is beneficial to enhancing the applicability of the multivariate matrix model.

Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this paper.

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