Multivariate matrix model for source identification of inrush water: A case study from Renlou and Tongting coal mine in northern Anhui province, China

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Abstract. Under the current situation of energy demand, coal is still one of the major energy sources in China for a certain period of time, so the task of coal mine safety production remains arduous. In order to identify the water source of the mine accurately, this article takes the example from Renlou and Tongting coal mines in the northern Anhui mining area. A total of 7 conventional water chemical indexes were selected, including Ca2+, Mg2+, Na++K+, Cl-, SO42-, HCO3- and TDS, to establish a multivariate matrix model for the source identifying inrush water. The results show that the model is simple and is rarely limited by the quantity of water samples, and the recognition effect is ideal, which can be applied to the control and treatment for water inrush.

1. Introduction
Due to the irreducibility of coal and the destruction of the environment, the consumption proportion of coal resources in China's energy structure gradually decreases with the adjustment of national energy structure (Xiao 2016; 2017a; 2017b). However, under the current situation of energy demand, coal is still one of the major energy sources in China for a certain period of time, so the safety task of mining in coal mine remains arduous. As one of the five major disasters (including gas, dust, water, fire and roof) in coal mine, water damage is a serious threat to coal mine safety production, which can cause huge economic losses and casualties when the mine floods.

Many coal mine water inrush accidents have taken place in China(Wu et al. 2013), therefore, the first thing to be done is to accurately identify the water source (Wen et al. 2014). Many scholars at home and abroad have studied the source identification of inrush water in coal mine from the perspective of hydrogeochemical, mainly including conventional water chemistry, trace elements and rare earth elements and isotopes methods(Dai et al.2017; Zhang et al. 2014; Cheng et al. 1995; Chen et al. 2010; Chen. 2014; Qin et al. 2014; Gui.2007). Due to the mining of coal mine for many years, meanwhile, the conventional water chemistry method is simple, fast and low cost, so that the coal mine accumulates a lot of conventional water chemical data. Therefore, the conventional water chemistry method has been widely used in discriminating the source of breakthrough water in coal mine. From simple contrast analysis on the types of water quality, feature components, etc., gradually developed into the multivariate statistical methods (such as cluster analysis, discriminate analysis etc.) and nonlinear analysis method, fuzzy mathematics and grey system theory, artificial neural network and extension identification method, etc.), have achieved a certain effect in the practical application.
Based on the previous research, this paper takes the example from Renlou and Tongting coal mine in the northern Anhui mining area, China, a total of 7 conventional water chemical indexes were selected, including Ca$^{2+}$, Mg$^{2+}$, Na$^{+}$+K$^+$, Cl$^{-}$, SO$_4^{2-}$, HCO$_3$ and TDS, to establish a multivariate matrix model for the identifying the source of inrush water, which can provide reference for the prevention and control of water in coal mine.

2. Hydrogeological conditions in mining area

The coal field in northern Anhui Province is an important energy base in China. There are more than thirty coal mines located in the area and more than 100 million tons of coals have been exploited per year (Sun et al. 2016). The research area is located in Linhuan coalfield, which belongs to the concealed coal mine. Based on Ordovician, this region developed the coal measures strata of Carboniferous and Permian, which were deposited after the movement of the earth's crust and the erosion of weathering. Previous study revealed that the aquifer system can be divided into: Cenozoic loose layer aquifer system (LA, including the first aquifer, the second aquifer, the third aquifer and the fourth aquifer), coal bearing sandstone aquifer system (CA), Taiyuan formation limestone aquifer system (TA) and the Ordovician limestone aquifer system (OA) (Gui HR. 2007; Sun et al. 2016). Sketch map of geological and groundwater aquifer system of the study area is shown in fig.1. Due to the third water-resisting layer mainly composed of clay, and it has good plasticity, strong expansibility, big thickness and stable distribution, the waterproof performance is very well, blocking the connection between the upper aquifer and the fourth aquifer (FA). Actually, for the Cenozoic loose aquifer, the fourth aquifer has the greatest impact on coal mining, it is the main supply source of the upper coal seam mining. Therefore, the groundwater systems related to the safe production of mining areas are mainly: FA, CA, TA and OA.

3. Research methods

The principle of multivariate matrix model is simple, and it is less subject to the number of samples and index of each sample type. What’s more, its reliability is high. Therefore, the multivariate matrix model has been applied in many disciplines, such as biology, ecology, systems engineering, power engineering, explosion safety theory and technology, etc (Li et al, 1992; Cai et al.1997; Huet al. 1998). As mentioned above, for identifying the source of inrush water from coal mines, many predecessors have made many attempts and achieved fruitful results. However, the use of multivariate matrix model to mine water inrush identification is very scarce (Sun et al. 2016).

The principle of the model is use multiple unknowns to set up matrix equations, and then calculate the unknowns based on the measured data and matrix operation. Its essence is approximate multivariate system of equations, and it is a special application of matrix equation in practical engineering(Sun et al. 2016). According to the general rule of mine water breakthrough, the water
source is generally composed of underground water. Therefore, the research goal of the multivariate matrix model of mine water source identification is the influence degree of each aquifer on the mine water inrush. It is mainly based on the measured data to identify the source of the water to be measured. The mathematical matrix of multivariate matrix model in mine water source recognition can be expressed as follows:

\[
C = \begin{bmatrix}
C_{11} & C_{12} & \cdots & C_{1n} \\
C_{21} & C_{22} & \cdots & C_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
C_{n-1,1} & C_{n-1,2} & \cdots & C_{n-1,n}
\end{bmatrix},
\]

\[
P = \begin{bmatrix}
P_1 \\
P_2 \\
\vdots \\
P_{n-1} \\
P_n
\end{bmatrix},
\]

\[
F = \begin{bmatrix}
F_1 \\
F_2 \\
\vdots \\
F_{n-1} \\
F_n
\end{bmatrix},
\]

In the formula, the matrix C is the water chemical index matrix corresponding to the aquifer; P matrix is the water chemical index matrix of the water sample to be tested, and the F matrix is the matrix of influence of each aquifer to the mine water breakthrough; \(C_{ij}\) (\(i = 1, 2... n-1; j = 1, 2... n\)) is the measured value of different water chemical indexes in aquifer; \(P_i\) (\(i = 1, 2... n\)) is the measured value of water chemical indexes of water samples for the identified, and \(F_i\) (\(i = 1, 2... n\)) is the degree of the impact of aquifers to the mine water breakthrough, that’s to say, the possibility of the water samples being tested for water samples belonging to each aquifers. The aquifer of the maximum value of \(F_i\) represents the main source of mine water bursting.

4. Establishment and application of multivariate matrix model

In the process of model construction, selecting proper water chemical indexes is particularly important for the source identification of inrush water accurately. Owing to each aquifer of mine has a variety of the chemical composition, and taking into account the importance of each component, the difficulty of testing, data validity and other factors, this article selects Ca\textsuperscript{2+}, Mg\textsuperscript{2+}, Na\textsuperscript{+}K\textsuperscript{+}, Cl\textsuperscript{-}, SO\textsubscript{4}\textsuperscript{2-}, HCO\textsubscript{3}\textsuperscript{-} and TDS, a total of 7 kinds of conventional water chemical indicators of mine inrush water for identification. We have collected routine hydrochemical data from the Ren Lou mine (RL) and the Tong Ting mine (TT) in the northern Anhui mining area, and the conventional water chemical indexes in mining area are shown in Table 1, and sample RL5 and TT5 represent the aquifer to be identified (UN).

| Sample | Na\textsuperscript{+}K\textsuperscript{+} | Mg\textsuperscript{2+} | Ca\textsuperscript{2+} | Cl\textsuperscript{-} | SO\textsubscript{4}\textsuperscript{2-} | HCO\textsubscript{3}\textsuperscript{-} | TDS | Aquifer |
|--------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-------|--------|
| TT1    | 176             | 72.36           | 80.0            | 124.5           | 540             | 107             | 1046  | FA     |
| TT2    | 753             | 11.94           | 24.8            | 104.1           | 1220            | 368             | 2315  | CA     |
| TT3    | 431             | 151             | 255             | 165.4           | 168             | 256             | 2815  | TA     |
| TT4    | 154             | 11.34           | 2.86            | 170             | 30              | 26.7            | 410.9 | OA     |
| TT5    | 155             | 8.51            | 6.81            | 171.9           | 29.78           | 108             | 425   | UN     |
| RL1    | 472             | 24              | 117.4           | 905.8           | 23.6            | 39.7            | 1562  | FA     |
| RL2    | 860             | 4.9             | 8.4             | 496.3           | 11.5            | 1139            | 2016  | CA     |
| RL3    | 460             | 98.9            | 235.1           | 996.2           | 225             | 334             | 2182  | TA     |
| RL4    | 10.5            | 5.8             | 80.5            | 1.9             | 19.8            | 275             | 256   | OA     |
| RL5    | 710             | 2.52            | 13.4            | 559.2           | 48.02           | 886             | 2219  | UN     |

In the first place, take Renlou coal mine as an example, expound the method of the model building. As mentioned above, the main source of water inrush in this mining area is FA, CA, TA and OA, namely, \(n = 4\), and the multivariate matrix model can be expressed as follows:

\[
C = \begin{bmatrix}
C_{11} & C_{12} & \cdots & C_{14} \\
C_{21} & C_{22} & \cdots & C_{24} \\
C_{31} & C_{32} & \cdots & C_{34} \\
1     & 1     & 1     & 1
\end{bmatrix},
\]

\[
P = \begin{bmatrix}
P_1 \\
P_2 \\
P_3 \\
P_4
\end{bmatrix},
\]

\[
F = \begin{bmatrix}
F_1 \\
F_2 \\
F_3 \\
F_4
\end{bmatrix},
\]

According to the principle of multivariate matrix model, this model is a four tuple model. Thus, selecting appropriate index as intermediate variable is critical to improve the accuracy of model. [17] chose TDS and the ionic index with significant linear relation as the intermediate variable to solve the problem. Considering each mining area groundwater aquifer system is complicated, if we according to
this method, may cause some mistakes. To improve the reliability of the model, according to the principle of matrix model, each group choose 3 kinds of conventional water chemical indicators, each indicator consists of Ca$^{2+}$, Mg$^{2+}$, Na$^{+}$+K$^+$, Cl$^-$, SO$_4^{2-}$, HCO$_3$-, TDS of the 7 groups of data, so that it can be composed of 35 groups of data. Taking Ca$^{2+}$, Mg$^{2+}$ and Na$^{+}$+K$^+$ as an example, the following matrix can be obtained:

$$
\begin{bmatrix}
\rho_1(Ca^{2+}) & \rho_2(Ca^{2+}) & \rho_3(Ca^{2+}) & \rho_4(Ca^{2+}) \\
\rho_1(Mg^{2+}) & \rho_2(Mg^{2+}) & \rho_3(Mg^{2+}) & \rho_4(Mg^{2+}) \\
\rho_1(Na^{+}+K^+) & \rho_1(Na^{+}+K^+) & \rho_1(Na^{+}+K^+) & \rho_1(Na^{+}+K^+) \\
1 & 1 & 1 & 1
\end{bmatrix}
\begin{bmatrix}
[F_1] \\
[F_2] \\
[F_3] \\
[F_4]
\end{bmatrix}
= 
\begin{bmatrix}
P_1 \\
P_2 \\
P_3 \\
P_4
\end{bmatrix}
$$

In the equation, $\rho_1$, $\rho_2$, $\rho_3$, $\rho_4$ represent the concentration of Ca$^{2+}$, Mg$^{2+}$, Na$^{+}$+K$^+$ in FA, CA, TA and OA, respectively; $P_1$, $P_2$ and $P_3$ represent the concentration of Ca$^{2+}$, Mg$^{2+}$, Na$^{+}$+K$^+$ in water samples to be measured; $F_1$, $F_2$, $F_3$ and $F_4$ represent the possibility of water samples belonging to each aquifers. To this point, the maximum of $F_1$, $F_2$, $F_3$ and $F_4$, and its aquifer has the greatest influence on the mine water breakthrough, which is represent the aquifer of inrush water source. By analogy, other indexes can be selected to calculate, respectively, and all of the results are listed in table 2. Combining all the discriminate results, we can complete the source identification of breakthrough water from the mine.

| Number | Ion population | $F_1$ | $F_2$ | $F_3$ | $F_4$ | Discriminate result |
|--------|----------------|------|------|------|------|--------------------|
| 1      | Ca$^{2+}$, Mg$^{2+}$, Na$^{+}$+K$^+$ | -0.678 | 0.8673 | -0.0138 | 0.2137 | CA |
| 2      | Ca$^{2+}$, Mg$^{2+}$, Cl$^-$ | 0.2007 | 0.8929 | -0.0658 | -0.0278 | CA |
| 3      | Ca$^{2+}$, Mg$^{2+}$, SO$_4^{2-}$ | -1.1099 | 0.769 | 0.1892 | 1.1518 | OA |
| 4      | Ca$^{2+}$, Mg$^{2+}$, HCO$_3$- | 2.8417 | 0.9559 | -0.1944 | -0.6241 | FA |
| 5      | Ca$^{2+}$, Mg$^{2+}$, TDS | 0.4341 | 0.9146 | -0.1107 | -0.238 | CA |
| 6      | Ca$^{2+}$, Na$^{+}$+K$^+$, Cl$^-$ | 0.5177 | 0.6720 | -0.2449 | 0.0547 | CA |
| 7      | Ca$^{2+}$, Na$^{+}$+K$^+$, SO$_4^{2-}$ | -0.5854 | 1.0399 | 0.1907 | 0.3542 | CA |
| 8      | Ca$^{2+}$, Na$^{+}$+K$^+$, HCO$_3$- | -0.5009 | 1.0118 | 0.1581 | 0.3323 | CA |
| 9      | Ca$^{2+}$, Na$^{+}$+K$^+$, TDS | -13.4396 | 5.3325 | 5.2588 | 3.8483 | CA |
| 10     | Ca$^{2+}$, Cl$^-$, ClO$_4^{-}$ | -0.2557 | 1.2105 | 0.1912 | -0.1460 | CA |
| 11     | Ca$^{2+}$, Cl$^-$, TDS | 0.3268 | 0.8054 | -0.1371 | 0.0043 | CA |
| 12     | Ca$^{2+}$, Cl$^-$, SO$_4^{2-}$ | -0.0552 | 1.0714 | 0.0771 | -0.0934 | CA |
| 13     | Ca$^{2+}$, SO$_4^{2-}$, HCO$_3$- | -2.6519 | -0.0281 | 0.1852 | 3.4939 | OA |
| 14     | Ca$^{2+}$, SO$_4^{2-}$, TDS | -0.3474 | 1.1639 | 0.1908 | -0.0073 | CA |
| 15     | Ca$^{2+}$, HCO$_3$-, TDS | 0.5668 | 0.8729 | -0.1624 | -0.2773 | CA |
| 16     | Mg$^{2+}$, Na$^{+}$+K$^+$, Cl$^-$ | 0.3475 | 0.6863 | -0.0965 | 0.0627 | CA |
| 17     | Mg$^{2+}$, Na$^{+}$+K$^+$, SO$_4^{2-}$ | -1.2139 | 1.3683 | 0.2151 | 0.6305 | CA |
| 18     | Mg$^{2+}$, Na$^{+}$+K$^+$, HCO$_3$- | 0.1778 | 0.7598 | -0.0623 | 0.1246 | CA |
| 19     | Mg$^{2+}$, Na$^{+}$+K$^+$, TDS | 3.5444 | -0.7099 | -0.7340 | -1.0990 | FA |
| 20     | Mg$^{2+}$, Cl$^-$, ClO$_4^{-}$ | -1.5634 | 3.3758 | 0.3032 | -1.1156 | CA |
| 21     | Mg$^{2+}$, Cl$^-$, HCO$_3$- | 0.2754 | 0.7875 | -0.0814 | 0.0185 | CA |
| 22     | Mg$^{2+}$, Cl$^-$, TDS | 0.0378 | 1.1219 | -0.0316 | -0.1287 | CA |
| 23     | Mg$^{2+}$, SO$_4^{2-}$, HCO$_3$- | -1.0478 | 0.4100 | 0.1734 | 1.4644 | OA |
| 24     | Mg$^{2+}$, SO$_4^{2-}$, TDS | -1.2932 | 1.8162 | 0.2350 | 0.2399 | CA |
| 25     | Mg$^{2+}$, HCO$_3$-, TDS | 0.5362 | 0.8628 | -0.1314 | -0.2654 | CA |
| 26     | Na$^{+}$+K$^+$, Cl$^-$, SO$_4^{2-}$ | 0.0454 | 0.7115 | 0.1658 | 0.0781 | CA |
| 27     | Na$^{+}$+K$^+$, Cl$^-$, HCO$_3$- | 0.0528 | 0.7108 | 0.1590 | 0.0773 | CA |
| 28     | Na$^{+}$+K$^+$, Cl$^-$, TDS | -0.6048 | 0.7645 | 0.7285 | 0.1088 | CA |
| 29     | Na$^{+}$+K$^+$, HCO$_3$-, TDS | -0.1858 | 0.6176 | 0.5812 | -0.0123 | CA |
| 30     | Na$^{+}$+K$^+$, SO$_4^{2-}$, HCO$_3$- | 0.0491 | 0.7097 | 0.1656 | 0.0764 | CA |
| 31     | Na$^{+}$+K$^+$, SO$_4^{2-}$, TDS | 1.1130 | 0.1538 | 0.1235 | -0.3903 | FA |
| 32     | Na$^{+}$+K$^+$, HCO$_3$-, TDS | -0.1858 | 0.6176 | 0.5812 | -0.0123 | CA |
| 33     | Cl$^-$, SO$_4^{2-}$, HCO$_3$- | 0.0475 | 0.7090 | 0.1653 | 0.0787 | CA |
| 34     | Cl$^-$, SO$_4^{2-}$, TDS | -0.1429 | 1.0226 | 0.1811 | -0.0608 | CA |
| 35     | Cl$^-$, HCO$_3$-, TDS | -1.9673 | 0.0109 | 2.3430 | 0.6128 | TA |

| 36     | Average of 31-35 | -1.9686 | 1.4155 | 0.7628 | 0.586 | CA |
According to Table 2, each ion population can be used to determine the possibility of the water samples to be measured belong to each aquifer. Similarly, take the ion population of $\text{Ca}^{2+}$, $\text{Mg}^{2+}$, $\text{Na}^+\text{K}^+$ for example, the possibility of bursting water samples belonging to FA, CA, TA and OA is -0.0678, 0.8673, -0.0138 and 0.2137, so the ion population shows that the source of the breakthrough water is CA. By calculating the results of other groups of ions, the source of the inrush water can be determined by the same way. According to the results of the calculation from Renlou coal mine, the source of inrush water for CA has 28 groups, derived from the FA have 3 groups, 3 groups from OA, and 1 group for TA (table 2 and 3). What’s more, the average also showed that the water inrush sources is CA. Similarly, using this analysis method, we can identify the main source of water inrush from Tongting coal mine. All of analysis results of water inrush from Renlou and Tongting coal mine in northern Anhui mining area are listed in table 3.

Table 3 Analysis of water inrush in northern Anhui mining area

| mine  | Aquifer | Quantity | average | Identify results |
|-------|---------|----------|---------|------------------|
| Renlou | FA      | 3        | -1.969  | CA               |
|       | CA      | 28       | 1.416   |                  |
|       | TA      | 1        | 0.763   |                  |
|       | OA      | 3        | 0.586   |                  |
|       | FA      | 4        | -0.045  |                  |
| Tongting | CA   | 0        | 0.138   | OA               |
|        | TA      | 2        | -0.068  |                  |
|        | OA      | 29       | 0.849   |                  |

In addition, according to the calculation results of table 2 and 3, some negative numbers appear in F1, F2, F3, and F4. The reason is that the chemical ions in each aquifer can be interactions between each other, such as the reaction between $\text{SO}_4^{2-}$ and $\text{Ca}^{2+}$, form $\text{CaSO}_4$ slightly soluble in water, as a result, the actual concentration of ions in the groundwater is biased against the results of the experiment, resulting in negative results. The identification of water source is ultimately based on the calculation results through the multivariate matrix model, selecting the largest one in $F_i$ (i=1, 2, 3, 4) as the source of water inrush. Namely, the negative number has no effect on the discriminate result, which is that the water inrush source of water sample is still accurate (Liu et al. 2014).

In order to verify the validity of the multivariate matrix model, R-type cluster analysis of conventional hydrochemical components of the four aquifers in two coal mines was carried out (Fig.2). As can be seen from Figure 2, the clustering results is ideal, and the 4 aquifers are clearly divided. The samples RL2 and RL5, TT4 and TT5 are clustered into one kind, which represent the CA and OA respectively.

![Fig. 2 R cluster analysis of Renlou and Tongting mine](image)

5. Conclusions

In this paper, a multivariate matrix model for mine water inrush is established by taking Renlou Mine and Tongting Mine of Wanbei Mining Area in Anhui Province as an example. The model is simple in principle and is limited in quantity and quantity of water samples, and the recognition effect is ideal. However, it is necessary to pay attention to that this paper is based on $\text{Ca}^{2+}$, $\text{Mg}^{2+}$, $\text{Na}^+\text{K}^+$, $\text{Cl}^-$, $\text{SO}_4^{2-}$,
HCO$_3^-$, TDS. And in the actual working process, due to the complexity of mine hydro-geochemical composition of groundwater system, involves a multitude of indicators. Therefore, the modeling index should be added in the follow-up study to improve the accuracy of the multi-matrix model for the source recognition of inrush water.

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