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TECHNICAL COMMUNICATION

A Multilevel Recognition Model of Water Inrush Sources: A Case Study of the Zhaogezhuang Mining Area

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Abstract
Discriminating water inrush sources efficiently and accurately is necessary to control water in coal mines. We combined the improved genetic algorithm (IGA) and extreme learning machine (ELM) methods and applied this new method to the Zhaogezhuang mining area. The IGA-ELM method effectively solved the complex non-linear problems encountered in identifying water sources and proved to have several advantages over conventional methodology. The IGA for the hill-climbing method was adopted to use the weights and thresholds of the ELM, which overcame the prematurity of the traditional genetic algorithm and the instability of the ELM model. Three types of water were identified in different aquifers of the Zhaogezhuang mining area: SO_4-Ca in the Laotang water, $SO_4 \cdot HCO_3$-Ca in the Ordovician limestone water, and HCO_3-Ca in the fractured sandstone roof of the no. 12 and 13 coal seams. The water sample recognition was 95% accurate, which proved that the water inrush source in the Zhaogezhuang mining area was accurately identified by the IGA-ELM model.

Keywords Water inrush source identification · Hydrochemical analysis · Improved genetic algorithm · Extreme learning machine · Zhaogezhuang mine

Introduction

With the increase in mining depths and intensity, water inrush accidents have become increasingly serious (Wu et al. 2017). This adversely affects coal production and threatens the safety of the miners. The Zhaogezhuang mine is located in the Guye District of Tangshan City, Hebei Province (Fig. 1). It is bounded by the depth of the Kaiping synclinal axis—1200 m—and is adjacent to and west of the Weishan mine, south of the Linxi mine, and north of Lianshan Mountain. The mine is located in the karst-fissure water disaster area of the Permo-Carboniferous coalfield in northern China. The Zhaogezhuang mine is divided into the Piedmont hydrogeological zone (I) and the Plain hydrogeological zone (II). Figure 1 shows the distribution of the five sub-districts and the aquifer and aquifuge of the Zhaogezhuang mine, based on the regional geology and hydrogeological characteristics. I_1 is a sub-district with a thrust structure and the

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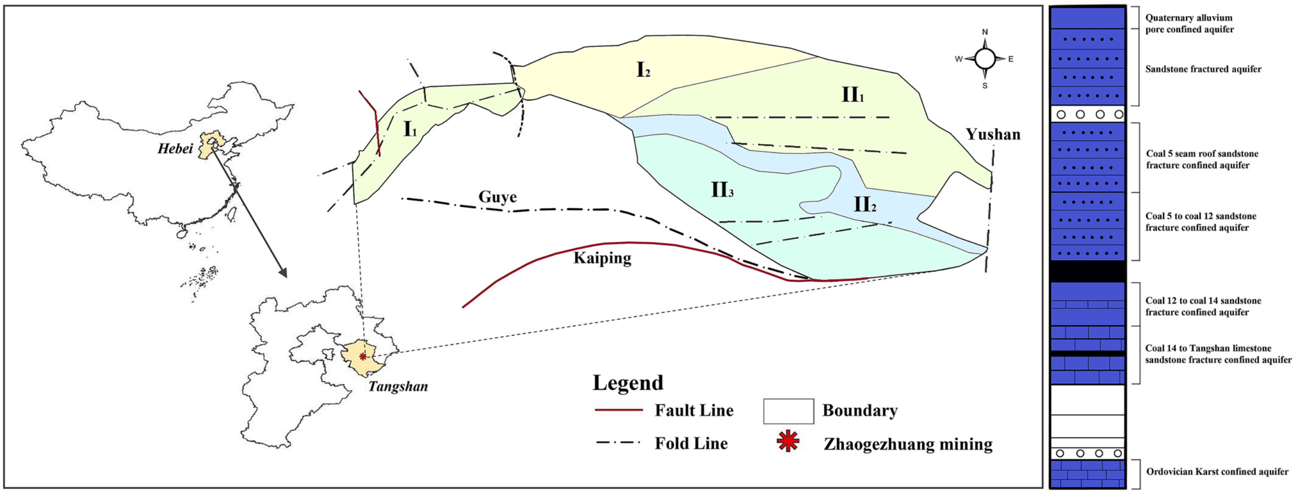

Fig. 1 General map of the study area location, geology and hydrogeological zone

only sub-district working under the Ordovician limestone in the Zhaogezhuang mine. I_2 is a steep sub-district, and the water in the overlying strata and floor fractures easily drains through the local fracture seepage zone in the fault development area.

The stratum of II_1 is gently inclined with normal and reverse faults, but no water inrush accident due to fault water diversion has ever happened, and the water inrush coefficient is less than 0.07 MPa/m. The stratum of II_2 is gently inclined with normal and reverse faults, but water inrush accidents can be caused by fault water diversion; the water inrush coefficient is less than 0.1 MPa/m but more than 0.07 MPa/m. The stratum of II_3 is gently inclined with large burial depth; the distance from the top of the Ordovician limestone is short, there are far fewer faults, the water inrush coefficient is more than 0.1 MPa/m, and the mining depth of II^3 is up to 1200 m. The water pressure of the Ordovician limestone is very high in this deep mine and is influenced by mine pressure, ground stress, geological structure, water pressure, and regional atmospheric precipitation. The water inrush coefficient of the Zhaogezhuang mine exceeds 0.1 Mpa/m, which has led to many inrush instances. In 1972, the $9132^{\#}$ coalface experienced a delayed water inrush that reached 3162 m^3/h, which caused serious losses (Wu et al. 2012; Guo and Guo 2010). In 2013, water inrush accidents occurred in the 10th and 11th crosscuts at 12 levels and the water peaked at 386.4 m^3/h (Lian et al. 2014). Water inrush is one of the biggest problems in this deep mine. However, despite a published analysis and evaluation of the water inrush characteristics of the Zhaogezhuang mine (Ding et al. 2010), there was little information available on the water source of the inrushes.

The hydrochemistry method (Wang and Shi 2019; Qian et al. 2018), the mathematical function analysis method (Huang et al. 2017; Li and Yang 2018; Gao 2012; Zhang et al 2018a, b; Gong and Lu 2018), the artificial intelligence analysis method (Wang et al. 2013; Xu et al. 2016), and other methods (Wu et al. 2019; Xu et al. 2018a, b) have been widely used to identify water inrush sources. The hydrochemical method requires significant differences in various hydrochemical factors to ensure accurate identification. The mathematical function analysis method, including the multivariate statistical method, the grey system method, and the fuzzy mathematical method, is simply calculated and easily operated, but its reliability needs to be further improved due to the influence of human factors and the inadequacy of weights determination. Artificial intelligence methods, such as Fisher linear discriminant (FLD), supported vector machine (SVM), Bayesian model, and the extreme learning machine (ELM) (Dong et al. 2019; Hobbs 1997; Tang 2018; Zhang and Yao 2020) are unaffected by human factors in the process of discrimination, which greatly increases discrimination accuracy, and has been widely recognized for water inrush source identification. To overcome the limitation of these methods, some optimization methods were gradually applied to improve the predictive ability of water inrush source identification. For example, the radial basis function (RBF) neural network provides an accurate prediction for the study of nonlinear or irregular problems, but has the problems of local optima, slow training speed, and low efficiency, which limits its application (Moody and Darken 1989; Zuo et al. 2020). The global optimization algorithms, particle swarm optimization (PSO) and the genetic algorithm (GA), are usually used to identify water inrush sources by optimizing the initial values of other methods but cannot guarantee that the solution is optimal (Shao and Li 2018; Zhang et al. 2018a, b). The grey wolf optimizer (GWO) method can be used has good global performance, but still has the disadvantages of slow convergence speed and weak local search ability (Mirjalili et al. 2014; Han et al. 2020). Given that, the objective of this study was to provide an effective mean, based on artificial intelligence, to solve water inrush sources in the Zhaogezhuang mine.

The ELM is a simple and efficient learning algorithm for a single hidden-layer feed-forward neural network (Huang et al. 2006) that has been used for water inrush source identification (Tang 2018). Since the initial weights and thresholds are randomly selected during the simulation training, the selected parameters can cause errors to the output weights and lead to instability of the ELM model. The accuracy of the results can be reduced and even misjudged. Xu et al. (2018a, b) used a GA to optimize the parameters of ELM to increase the accuracy of water source identification. However, there were still problems with this traditional GA, such as a slow convergence speed, a large computation load, and prematurity (Wang and Kozo 2007). Further improvement was necessary.

The hill-climbing method is a kind of local optimization search method (Chai and Zhou 2014). An improved genetic algorithm (IGA), introducing the hill-climbing method into the GA iteration process to optimize the individuals searched by GA locally, can increase the convergence efficiency and accuracy of GA. An IGA-ELM model that uses the IGA to optimize the initial weights and the thresholds of ELM can overcome the disadvantages of the traditional ELM, such as an unstable network and slow convergence speeds, and improve the performance of this ELM. Lv et al. (2018) applied the IGA-ELM model to short-term load forecasting and showed that it had the advantages of a fast learning speed, strong network stability, and better generalized performance.

IGA-ELM can effectively solve the complex non-linear problems encountered in identifying water sources. This study was undertaken to present a multilevel recognition model based on hydrochemical analysis and the IGA-ELM model for rapid identification of water inrush sources in the Zhaogezhuang mining area. The typical water samples of each aquifer in the study area were determined using the Piper trilinear diagram.

The hydrochemical information was obtained from the hydrogeological report and the field investigation data of the Zhaogezhuang mining area, including 70 groups of water samples from a Laotang water sample (I), an Ordovician lime water sample (II), 12 coal fissure aquifer water samples (III), and 13 coal fissure aquifer water samples (IV). Na^+, Ca^{2+}, Mg^{2+}, Cl^-, SO_4^{2-}, and HCO_3^- were selected as the discriminant indexes (Table 1).

Methods

Framework of the Multilevel Recognition Model of Water Inrush Source

A multilevel recognition model for the rapid identification of water inrush sources in the Zhaogezhuang mining area was implemented using the following steps:

Step 1 Mine water sample data were collected, and the water chemical characteristics of each aquifer were analyzed using the Piper trilinear diagram. Abnormal water samples that deviated from the stratum center were identified and removed. The remaining water samples were deemed as the representative water samples of each aquifer.

Step 2 The representative water sample was encoded. A GA was used for selection, crossover, and mutation operations, and the hill-climbing method was used to find the optimal chromosome, which was selected as the initial weights and thresholds of the ELM.

Step 3 The normalized function of MATLAB was used to normalize the data to eliminate the order of magnitude difference between the variables. The normalized data was coded by abstracting the weights of the input layer and the threshold of the hidden layer of the network into a chromosome, and six hydrochemical indexes were input—that is, the number of nodes in the input layer of the network was set to 6. Four types of water samples were output—that is, the number of nodes in the output layer of the network was 4. By adjusting the parameters through the training results, the number of hidden layer nodes was determined to be 25, the length of chromosomes of the genetic algorithm was determined to be 49, the maximum iteration number was determined to be 100, and the population size of each generation was determined to be 20. The individuals with high fitness in the initial population were selected to form a new population using the roulette wheel method; the mutation probability was 0.05 and the crossover probability was 0.7. The mutation was carried out in the optimal direction through local optimization of the hill-climbing algorithm in the process of mutation and iterated back and forth until the end condition was satisfied or iterated to 100 generations. Finally, the chromosomes with the best fitness were identified and decoded as the optimal weights and thresholds of the ELM, and MATLAB was used for simulation

Table 1 Water sample data of the Zhaogezhuang mine

Groups	Content of each hydrochemical index (mmol/L%)						Water sample types
	Na^+	Ca^{2+}	Mg^{2+}	Cl^-	SO_4^{2-}	HCO_3^-	
1	51.51	26.48	19.62	9.29	8.56	82.15	I
2	59.10	23.50	16.11	8.67	11.54	78.69	I
3	11.05	66.34	22.23	1.5	81.28	17.21	I
4	4.36	54.83	40.66	2.68	66.49	30.83	I
5	10.7	54.64	34.18	11.31	70.14	17.54	I
6	5.86	48.45	45.06	1.79	81.84	16.37	I
7	8.91	53.43	37.46	8.45	60.47	31.08	I
8	6.05	54.13	38.71	1.81	76.57	21.62	I
9	5.69	51.7	41.83	1.65	81.41	16.85	I
10	18.02	40.9	40.82	1.75	81.83	16.25	I
11	6.95	44.44	48.09	1.44	85.55	13.00	I
12	2.54	50.85	45.59	2.46	83.76	13.78	I
13	6.09	49.63	43.92	1.58	81.75	16.67	I
14	7.62	49.75	42.4	1.66	81.88	16.46	I
15	7.86	48.59	43.2	1.54	82.39	16.07	I
16	0.73	52.53	46.73	1.19	93.24	4.73	II
17	4.72	61.35	33.83	3.26	48.6	48.13	II
18	6.14	58.45	35.16	3.22	49.56	47.21	II
19	10.46	64.28	24.96	13.06	15.71	60.34	II
20	11.15	67.79	21.06	11.36	19.93	58.08	II
21	11.88	66.20	21.91	13.77	25.31	51.48	II
22	8.8	65.27	24.18	11.16	14.74	61.63	II
23	12.49	60.85	24.98	12.57	23.62	52.27	II
24	10.69	51.17	37.61	9.53	14.63	69.08	III
25	5.97	54.01	39.52	9.22	13.66	76.64	III
26	8.13	55.92	35.51	9.36	11.97	78.18	III
27	9.74	51.28	38.29	8.45	13.95	76.99	III
28	8.36	52.14	39.12	9.41	13.57	76.96	III
29	1.54	67.1	31.1	8.76	14.58	72.14	III
30	9.85	52.61	36.57	8.44	15.71	75.23	III
31	10.31	51.09	38	8.65	14.66	76.08	III
32	9.49	52.49	37.5	8.77	12.88	77.79	III
33	7.71	55.31	36.37	8.67	13.17	77.79	III
34	9.41	50.43	38.87	8.42	14.59	76.60	III
35	12.9	50.31	36.22	9.04	12.34	78.23	III
36	15.11	47.81	36.85	8.4	13.81	77.49	III
37	8.08	60.91	31.01	8.56	15.44	72.94	III
38	8.43	59.97	31.55	8.95	16.16	71.8	IV
39	8.16	58.08	33.76	8.87	14.91	72.26	IV
40	12.67	51.17	35.77	10.99	12.71	74.11	IV
41	7.77	57.13	34.88	9.03	13.32	74.16	IV
42	8.80	57.5	33.62	9.94	15.3	70.81	IV
43	4.63	58.01	37.36	10.96	17.03	69.47	IV
44	3.78	61.88	34.32	5.71	16.71	73.42	IV
45	9.40	59.59	30.95	9.54	15.3	71.23	IV
46	2.92	61.30	35.78	9.56	15.85	71.05	IV
47	7.33	60.34	32.33	8.61	16.4	70.84	IV
48	11.95	56.99	30.87	9.01	14.93	73.84	IV
49	6.80	62.73	30.13	8.57	16.88	70.61	IV

Table 1 (continued)

Groups	Content of each hydrochemical index (mmol/L%)						Water sample types
	Na^+	Ca^{2+}	Mg^{2+}	Cl^-	SO_4^{2-}	HCO_3^-	
50	5.58	64.36	29.94	8.8	16.42	71.25	IV
A1	11.81	49.18	37.87	3.08	71.87	21.7	I
A2	12.36	52.11	34.83	2.92	72.3	22.78	I
A3	11.77	50.85	36.88	2.51	78.22	19.24	I
A4	10.37	49.73	39.47	2.12	83.91	13.9	I
A5	9.16	50.23	40.17	2.13	82.78	15.09	I
A6	6.93	57.86	39.66	4.47	53.01	41.86	II
A7	6.52	59.38	40.44	5.61	51.8	41.7	II
A8	5.53	60.29	38.49	4.6	50.74	44.62	II
A9	5.87	64.68	29.45	8.25	20.93	68.48	II
A10	6.26	58.53	39.73	5.19	49.24	43.23	II
A11	12.96	48.26	38.24	9.65	13.88	76.17	III
A12	9.69	52.5	37.16	9.48	10.86	79.58	III
A13	12.63	47.16	39.19	9.20	14.77	75.28	III
A14	14.49	46.62	37.7	9.41	13.74	76.91	III
A15	13.28	49.67	37.85	10.03	12.43	77.05	III
A16	5.92	61.89	31.72	8.61	15.95	70.99	IV
A17	8.35	58.11	33.54	8.75	15.54	71.92	IV
A18	9.60	60.39	30.01	8.65	16.38	71.43	IV
A19	8.43	58.21	30.85	8.7	16.12	71.22	IV
A20	9.27	57.23	30.5	8.77	15.92	70.8	IV

training, output water sample prediction results, and algorithm completion.

IGA-ELM Model

The IGA method uses the hill-climbing method to improve the performance of the traditional GA. It makes use of the local optimization characteristics of the hill-climbing algorithm to select the offspring population generated by the selection, crossover, and mutation operations of the genetic algorithm, so that the GA develops continuously in the global optimum direction in the process of reciprocating iterations. Thus, the individuals with the best fitness in the population can be used as the initial weights and thresholds of the ELM, which overcomes the shortcomings of traditional GA and improves the stability and prediction accuracy of the ELM. Lv used the IGA-ELM method to verify the active load data of the main transformer, Rose No. 1, in Zhengzhou City, Henan Province (Lv et al. 2018); the results showed that the IGA-ELM method has a fast learning speed, strong network stability, and general performance. Thus, it can be used to improve the accuracy of the water inrush source identification model to a certain extent. The training speed of this method is fast, and the number of iterations of the model is less, enabling quick and accurate inrush source identification in mine water inrush.

Simulation training of the IGA-ELM

(1) The initialization population was determined as follows:

$$X = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix} = \begin{bmatrix} a_{11} & \cdots & a_{1A} & b_{11} & \cdots & b_{1B} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ a_{m1} & \cdots & a_{mA} & b_{m1} & \cdots & a_{mB} \end{bmatrix} \quad (1)$$

where a_{kg} is the input weight and b_{kh} is the hidden neuron threshold (Ding et al. 2015).

(2) Selection, crossover, and mutation operations were carried out by the genetic algorithm, and local optimization of offspring individuals was carried out by the hill-climbing method.

(3) Simulation training was carried out using the optimal individuals as the input weights and thresholds of the ELM:

$$\sum_{i=1}^{L} \beta_i g\left(W_i \times X_j + b_i\right) = o_j \quad j = 1,\ 2, \dots,\ N \quad (2)$$

where $g(x)$ is the activation function, $W_i = [w_{i1}, w_{i2}, \dots, w_{in}]^T$ is the input weight, β_i is the output weight, and b_i is the bias of the ith hidden layer unit. $W_i{*}X_j$ represents the inner product of W_i and X_j (Wang and Liu 2015).

Results and Discussion

Hydrochemical Characteristics of the Aquifers

Figure 2 shows that Ca^{2+} and Mg^{2+} are the main cations in the Laotang water samples, with the Ca^{2+} exceeding 80%; the anions are mainly SO_4^{2-} and the water samples are mainly located in the upper left rhombic region. Thus, the hydrochemical type of the Laotang water samples is mainly SO_4-Ca. The cations in the Ordovician lime water samples are mainly Ca^{2+}, the anions are mainly SO_4^{2-} and HCO_3^-, and the water quality type is $SO_4{\cdot}HCO_3$-Ca. The dominant cation is Ca^{2+} and the dominant anion is HCO_3^- in the fractured water samples of the roof sandstones of the12 and 13 coal seams, so the water quality type of the two samples is HCO_3-Ca.

It can be seen that the water samples of Groups 1, 2, and 16 in Laotang deviate from the stratum center in the Piper trilinear diagram and were quite different from the water quality of other water samples, so they were excluded. Based on an analysis of Fig. 2 (III), (IV), there was no obvious water quality difference between the III and IV water samples, which were not excluded. Therefore, the training

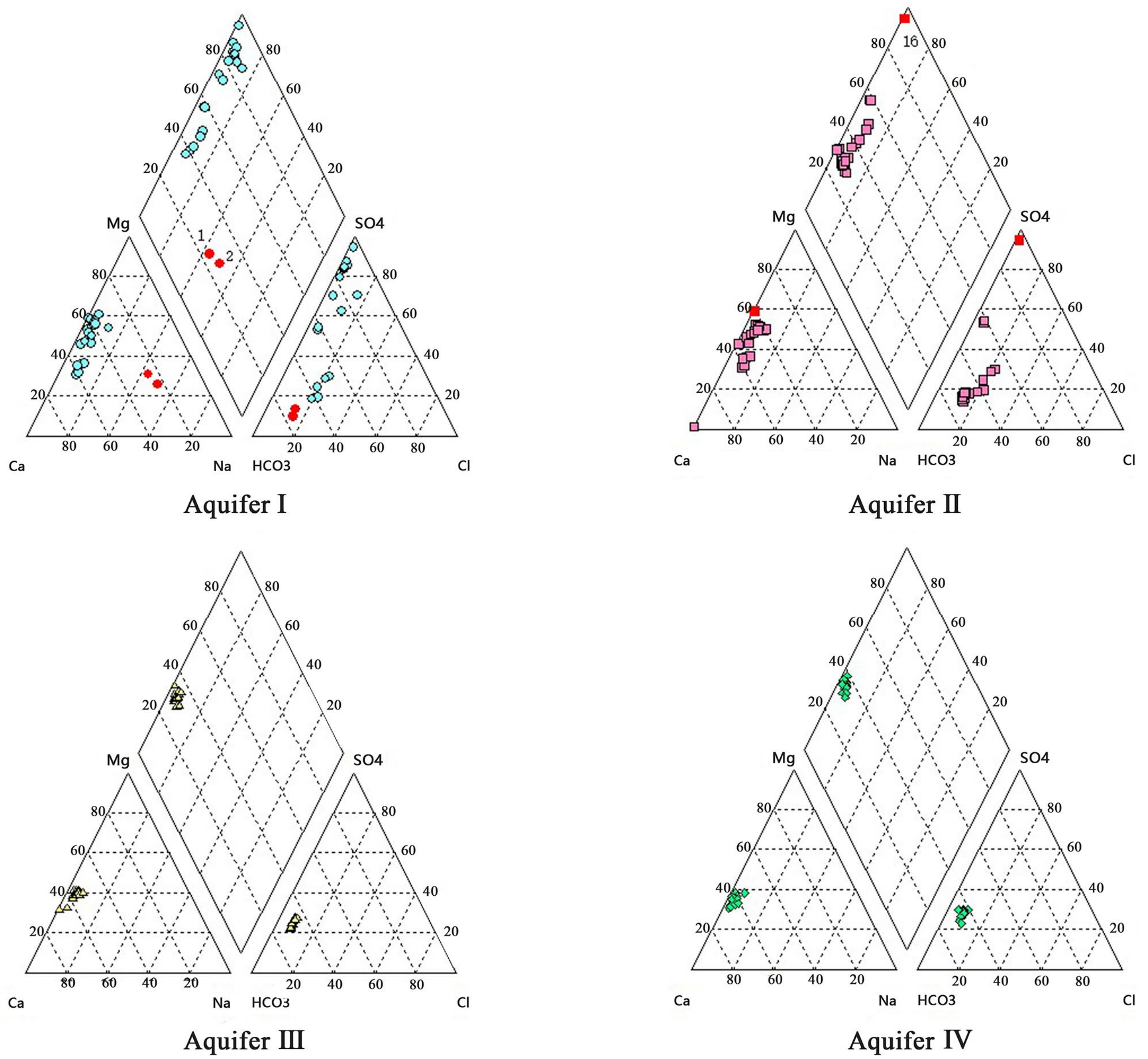

Fig. 2 Piper trilinear diagram of water samples from Aquifer I, II, III, and IV. Note: the red water samples presented the abnormal water samples while the others were the normal ones

samples from the measured data in Table 1, except for Groups 1, 2, and 16, were taken as typical of the four kinds of water samples.

Analysis of IGA-ELM

To ensure the accuracy of the model, the typical water samples determined by hydrochemical analysis were trained by simulation. Figure 3 shows the testing sample recognition results: the testing accuracy rate of the IGA-ELM model was 100%, while the ELM model was 87.23% accurate, since six groups of water samples were misidentified.

On this basis, the empirical application of the model was carried out. The 20 groups of water samples to be tested in the Zhaogezhuang mining area were substituted into the IGA-ELM model for simulation training. Except for the Group 9 water samples (from the Ordovician limestone), the recognition results of the water samples were consistent with the actual water samples, so the recognition accuracy was 95%. When the traditional ELM was used to train the same water samples, the accuracy of the ELM was only 75 (Figs. 4 and 5).

In the process of simulation training, the GA was improved by the hill-climbing method. When the optimal

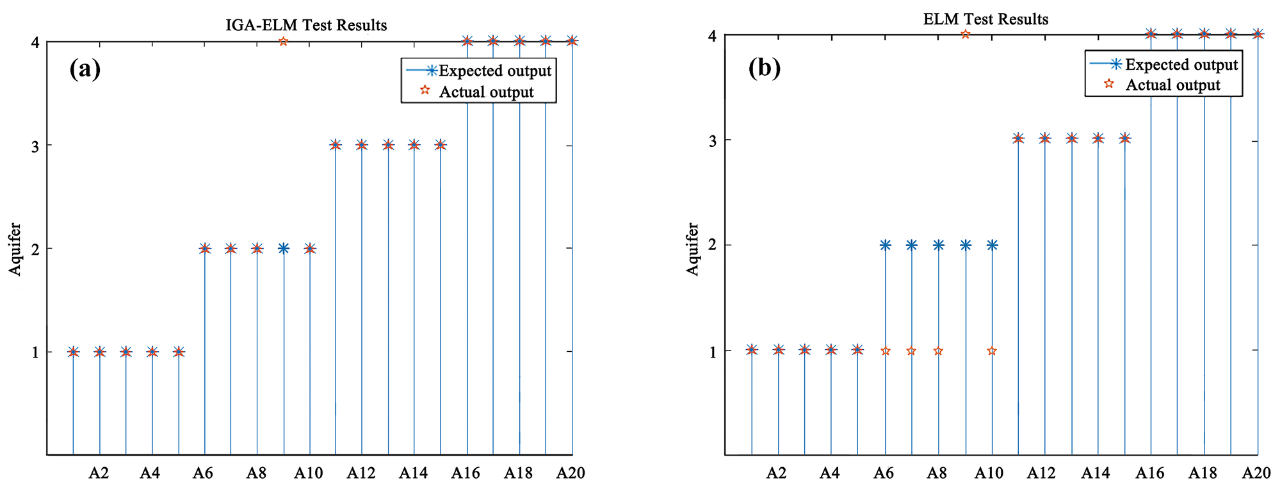

Fig. 3 Testing sample recognition results; **a** IGE-ELM recognition, **b** ELM recognition

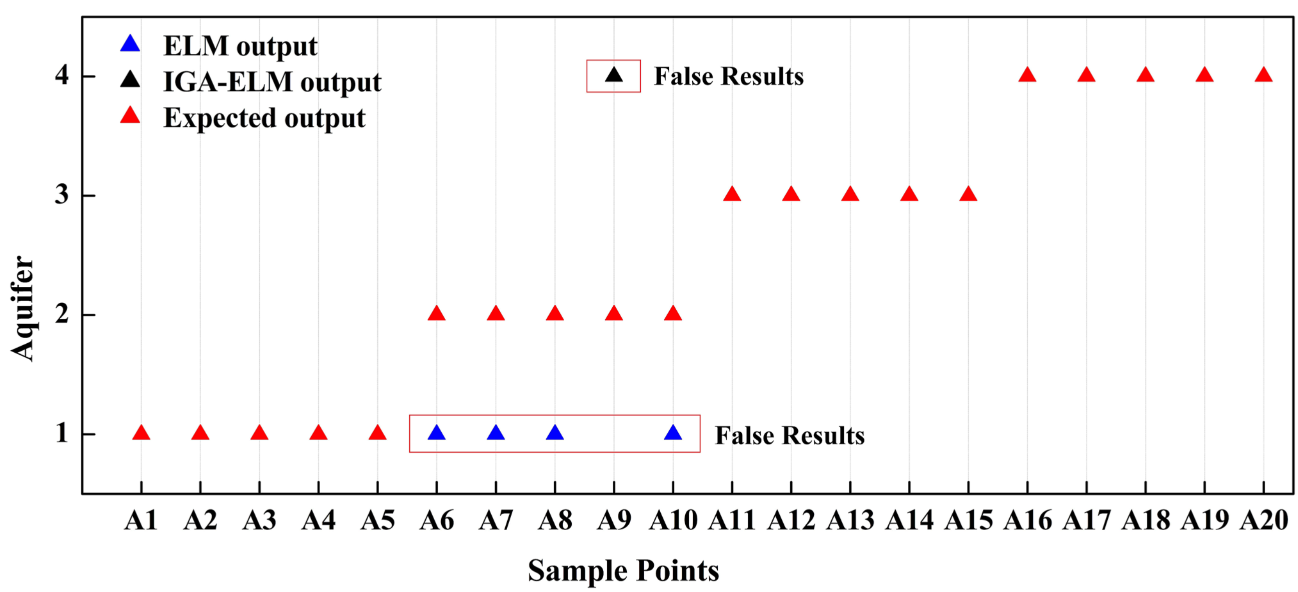

Fig. 4 Training sample recognition results; **a** IGE-ELM recognition, **b** ELM recognition

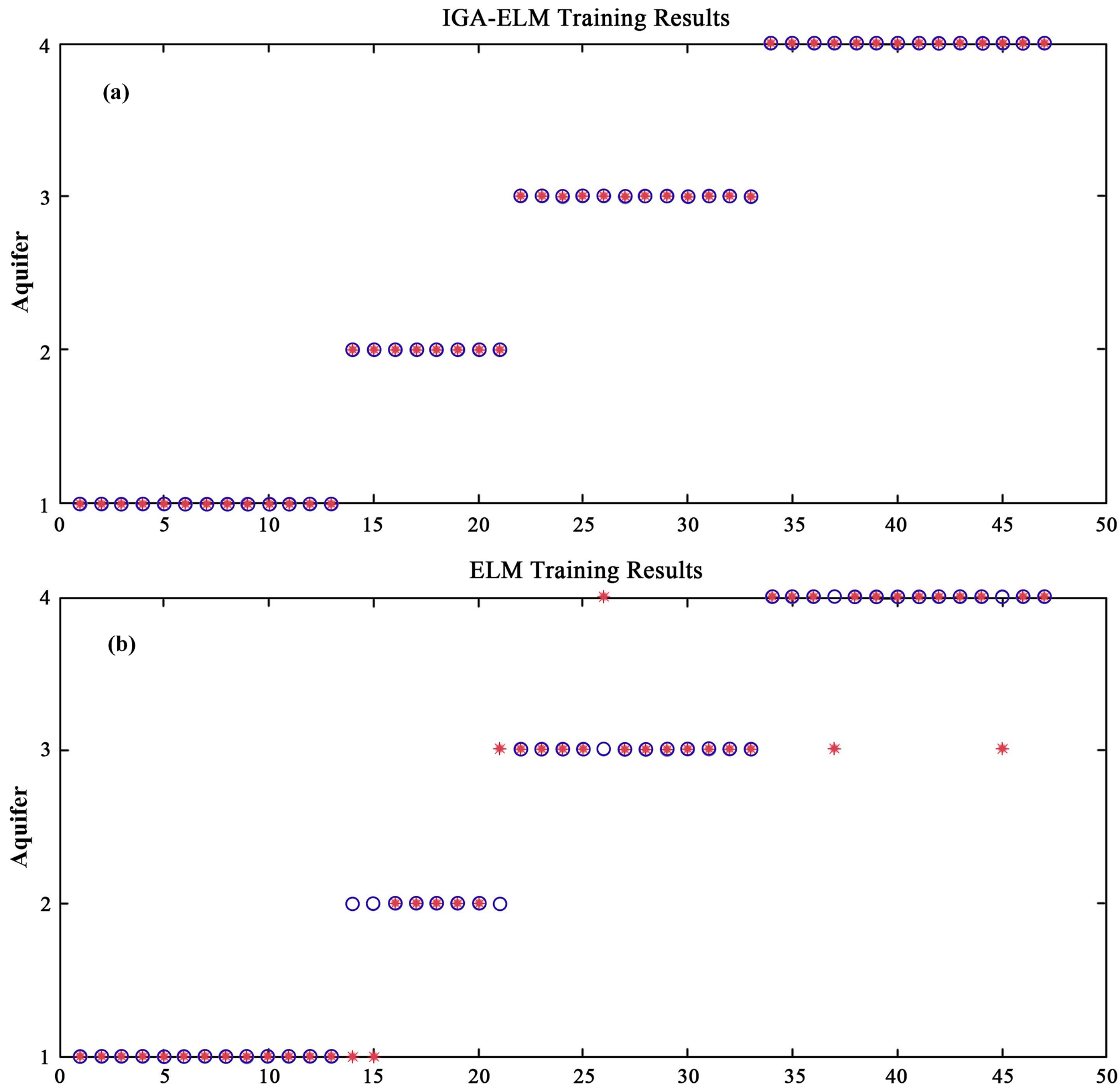

Fig. 5 Comparison of ELM and IGA-ELM recognition

solution was found, the optimization process ended, and the ELM prediction began. The training speed of the whole process was faster (less than a minute for the IGA-ELM recognition model) and the results were more accurate. The traditional ELM obviously did not perform as well as the optimized algorithm due to its unstable network and repeated misjudgements.

The two models were each tested three times. The mean average absolute percentage error of the traditional ELM algorithm was 1.73E − 03, while that of the IGA-ELM was only 5.33E − 04. Again, the IGE-ELM was more accurate, had better prediction ability, and was practical to use.

Limitations of the Study

There may be errors in the study of the whole mining area because of the limited data used to establish the model (Huang and Wang 2018). Therefore, the hydrogeological conditions of the aquifer in the study area should be fully analyzed, and more data should be collected to improve the training set of the model, so as to ensure the stability of the model training and the accuracy of the results. Considering that the Group 9 Ordovician limestone water was misjudged during the training process of the model, it may be that the chemical composition of the water sample changed greatly with the time series, and the water chemical index of the aquifer varied during long-term groundwater movement. Thus, the reliability of the data needs to be guaranteed in applications of this model in the future.

Conclusions

Based on hydrochemical analysis and the IGA-ELM model, this paper proposes an integrated intelligent recognition model to rapidly identify the water inrush sources in the Zhaogezhuang mining area. The main conclusions are as follows:

(1) The hydrochemical type of the Laotang water was SO_4-Ca, the Ordovician limestone was $SO_4 \cdot HCO_3$-Ca, and the water in the fractured sandstone roof of the no. 12 and 13 coal seams was HCO_3-Ca.
(2) The multilevel recognition model of the water inrush source was used to train 20 groups of water samples in the Zhaogezhuang mine, and the accuracy of the results was 95%.
(3) IGA-ELM overcomes the instability of the traditional ELM model network and has greater accuracy and less error. Therefore, the model has some application value in mine water inrush source identification.

However, this recognition model still has shortcomings (e.g. the discriminant results were incorrect) and should be further improved.

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