Prediction of the Confined Water Rising Zone in a Coal Floor Based on Fuzzy Theory (Fuzzy) – Gray Relation Analysis (GRA) – Particle Swarm Optimization(PSO) – Support Vector Regression (SVR)

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Abstract

The confined water rising zone and water inrush from the floor are closely related. In this paper, based on the collected samples of North-China-type coalfields, after the nondimensional disposal of the influencing indices by Fuzzy Theory (Fuzzy), four main indices were selected by the Gray Relation Analysis(GRA): aquifuge index, water pressure index, permeability index and structural index. The (Particle Swarm Optimization) PSO was used to optimize the parameters of the (Support Vector Regression) SVR; then, the nonlinear regression model was established by the SVR to predict the confined water rising zone based on MATLAB. Compared with other methods, the Fuzzy-GRA-PSO-SVR model has good generalization and can be applied to field prediction.

Keywords: Fuzzy-GRA-PSO-SVR model, confined water rising zone, water inrush from floor, Ordovician limestone aquifer

Introduction

In China, the karst of Ordovician limestone aquifer is abnormally developed (Qiu 2017) with the characteristics of strong supply, high water pressure and big water content. When the water resistance ability of the coal seam floor is weak, the water in the Ordovician limestone aquifer will directly pour into the working face under the action of high static water pressure and easily cause a mine water disaster. The confined water rising zone (Fig. 1) (Shi 2000) refers to the elevation of confined water in the Ordovician limestone aquifer along the split or fault fracture zone of a lower aquifer under the action of high water pressure, which is a key factor to evaluate the safety of coal seam mining above the confined aquifer. A higher confined water rising zone has a greater possibility of water inrush from the floor. Its characteristics are that the rock is in an elastic-plastic behavior, the fissure has become a channel of water inrush, and the continuity of the rock is poor.

In the current technology, there are few records about the prediction method of the confined water rising zone. Xiaoge Yu predicted the confined water rising zone for the first time based on the BP neural network model (Yu 2014). However, this method requires a large quantity of measured data as training samples and has the problems of slow convergence rate and local minimization. In this paper, we establish a Fuzzy-GRA-PSO-SVR model to accurately predict the confined water rising zone, which can provide the theory gist for the prediction of the Ordovician limestone water inrush and precise mining of coal mines.

Influencing Indices

Workface index (W): The inclined length of the working face reflects the strength of the coal seam mining. Generally, a wider working

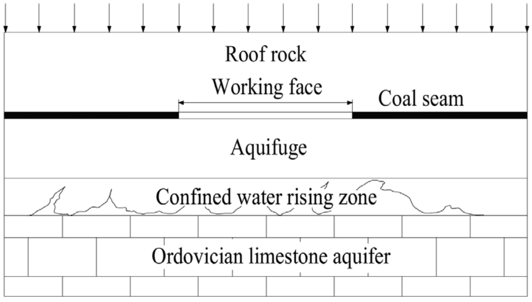

Figure 1 Location map of the confined water rising zone

face corresponds to a greater mining intensity of the coal seam, and a more unstable stress environment of the strata is more conducive to the development of cracks in the confined water rising zone.

Aquifuge index (M): The aquifuge refers to the rock and soil layer with poor permeability. A thicker aquifuge has lower possibility of water inrush from the floor, which is more unfavorable to the development of the confined water rising zone.

Water pressure index (P): The water pressure of the Ordovician limestone aquifer provides the driving force for its development. The data are obtained by the underground water level conversion of the Ordovician hydrogeological hole.

Depth index (D): The buried depth of the coal seam is the vertical distance from the earth's surface to the middle of the roof and floor of the coal seam. It affects the surrounding pressure environment, mining way, mining intensity, etc.

Permeability index (K): A larger permeability coefficient corresponds to a smaller resistance that the confined water must overcome along the way, which is more conducive to the development of the confined water rising zone.

Structural index (F): The fault intensity index (FII) is the sum of the products of the extension length of all faults in the unit area and their drop height. This index can comprehensively reflect the fault complexity in one general area. The faults provide space for the development of the confined water rising zone, reduce the resistance along the channel and directly affect the development of the confined water rising zone.

Data

In this paper, 25 samples from North China-type coalfields were collected (tab. 1), of which the first 20 were used as training samples, and the last 5 were used as testing samples. The distance between the initial water levels of the Ordovician injection grouting drill hole and the maximum normal of the top surface of the Ordovician limestone aquifer is set as the practically measured value of the original confined water rising zone.

Model Establishment

The GRA refers to the level of similarity between two sequences. A closer relational degree to 1 indicates a better relativity. The indices with the gray relational degree greater than 0.8 were taken as the main influencing indices. We programmed by using MATLAB software and calculated the relational degrees as follows (tab. 2).

The 4 main influence indices (P/MPa; $K/10^{-13}m^2(Pa\cdot s)^{-1}$; F; M/m) and the confined water rising zone of the 20 training samples in tab. 1 were normalized using MATLAB.

SVR (Zhang 2018) has functions of nonlinear modeling, nonlinear prediction, and optimization control. Let the data samples be an n-dimensional vector, the training data set is $\{(x_i, y_i), \cdots, (x_l, y_l)\}$, $x_i \in R^n, y_i \in R, i = 1,2,3,\cdots,l$; then, the regression function used to fit the function of sample data is:

$$f(x) = \omega \times \Phi(x) + b \tag{1}$$

where the undetermined parameters ω and b are the weight vectors and offset value, respectively. A punitive factor C (C>0) is

Table 1 Measured Data of North China-type Coalfields

	number	W/m	M/m	P/MPa	D/m	$K/10^{-13}m^2(Pa \cdot s)^{-1}$	F	H/m
training sample	1	80	55.3	3.1	412	1.02	0.12	6.1
	2	85	65.4	7.8	1035	2.14	0.21	16.0
	3	95	80.3	4.5	850	3.56	0.16	13.9
	4	97	95.6	9.9	715	4.05	0.81	24.5
	5	82	110.1	6.4	550	5.2	0.75	25.8
	6	100	50.1	6.2	856	3.99	0.53	17.3
	7	105	70.3	3	700	5.43	0.45	12.1
	8	115	82.1	7.5	559	1.22	0.56	12.8
	9	107	94	4.6	400	2.00	0.32	12.2
	24	160	95	6.4	1240	1.6	0.24	9.4
	11	120	50	9.0	587	2.13	0.69	18.1
	12	120	65	6	412	3.56	0.78	19.9
	13	125	80	2.9	1100	4.20	0.36	11.4
	14	110	95	7.1	800	5.1	0.9	23.4
	15	120	110	4.7	720	1	0.25	7.2
	16	140	45	4.1	1124	5	0.55	15.1
	17	135	66	9.2	853	1.81	0.34	11.6
	18	140	78	6	700	2	0.44	12.1
	19	140	84	3.1	540	3.40	0.22	10.6
	20	150	110	7.7	450	4	0.51	28.2
test samples	21	160	53	7	700	3.1	0.59	17.9
	22	200	66	4.5	590	4.04	0.66	17.6
	23	220	74	9.2	400	5.2	0.96	33.1
	24	100	100	9.8	1000	3.00	0.73	21.3
	25	160	102	3.2	870	2.6	0.29	8.7

Table 2 Relational degree with the confined water rising zone

	W/m	M/m	P/MPa	D/m	$K/10^{-13}m^2(Pa \cdot s)^{-1}$	F
Relational degree with the confined water rising zone	0.7926	0.8563	0.9750	0.3640	0.9678	0.9614

introduced, and equation 1 can be expressed as the following constrained optimization problem:

$$\text{Min}: \frac{1}{2}\omega^2 + C\sum_{i=1}^{l}(\xi + \xi^*) \tag{2}$$

where ξ is the relaxation factor.
The Lagrange multiplier is used to transform equation 2 into its dual problem:

$$\text{Max}: W(\alpha,\alpha^*) = -\frac{1}{2}\sum_{i,j=1}^{l}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)K(x_i,x_j) + \sum_{i=1}^{l}(\alpha_i-\alpha_i^*)y_i - \sum_{i=1}^{l}(\alpha_i+\alpha_i^*)\varepsilon \tag{3}$$

$$k(x_i,x) = \exp\left\{-|x-x_i|^2/2\sigma^2\right\},\quad 1/\sigma^2 = g \tag{4}$$

where $K(x_i,x_j) = \left\lfloor \Phi(x_i),\Phi(x_j) \right\rfloor$ is called the kernel function, and α and α^* are the corresponding support vectors. After solving equation 3 and obtaining the corresponding a and b, the optimal fitting function can be determined as:

$$f(x)=\sum_{i=1}^{l}(\alpha_i-\alpha_i^*)K(x_i,x_j)+b \qquad (5)$$

The PSO is used to select the support vector regression parameters, which can avoid the blindness and randomness of artificial selection, and improve the efficiency and accuracy of the parameter selection. C controls the error of the training samples. A larger C corresponds to a better training effect but also a lower generalization ability. Width coefficient g reflects the degree of correlation between support vectors. A larger g indicates a looser relation among the support vectors. Therefore, the selection of appropriate C and g is the key to ensure the regression of the SVR.

Based on the MATLAB platform, the initial population parameters were set by the PSO; then, the learning sample fitting graph (Fig. 2) was obtained by sample mapping calculation and linear fitting training. The learning effect was evaluated according to the relative error of the fitting degree. If the average relative error is smaller, then the learning effect is good. If the average relative error is larger, the original population generates a new population through iteration, and the second step is to reoptimize the SVR parameters using the PSO. Finally, after many studies, the optimal parameters c and g are found.

Establishment of the multiple linear regression formula

In this paper, the weight function of the MATLAB software is used to calculate the weight of the main influence indices. The weights of the aquifuge index, water pressure index, permeability index, and structural index are 0.0964, 0.1907, 0.3386, and 0.3743, respectively.

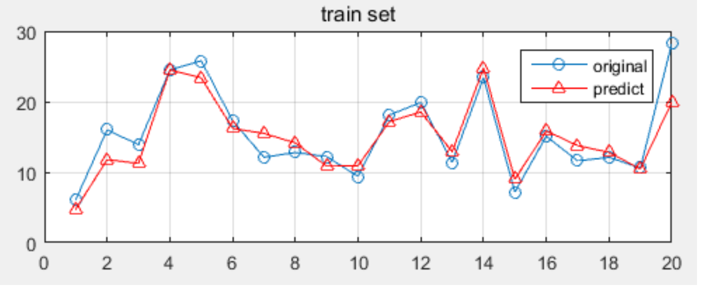

Figure 2 *Fitting Chart of the Training Samples of the Fuzzy-GRA-PSO-SVR model*

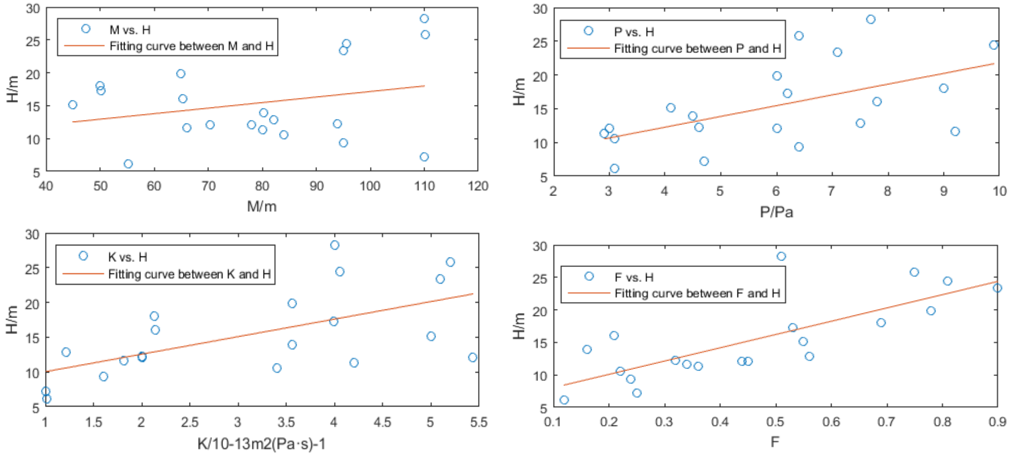

Figure 3 *Fitting curve between the confined water rising zone and each influence index*

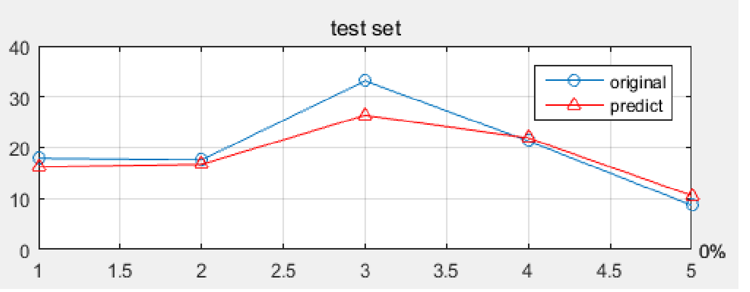

***Figure 4** Fitting Chart of the Test Samples of the Fuzzy-GRA-PSO-SVR model*

According to the fitting curve of Fig. 3, the linear fitting formulas between the main influence index and the development height of the confined water rising zone are as follows:

$$H_a = 0.0843M + 8.7225 \quad (6)$$

$$H_b = 1.595P + 5.8787 \quad (7)$$

$$H_c = 2.5225K + 7.5132 \quad (8)$$

$$H_d = 20.434F + 5.9956 \quad (9)$$

Based on the linear fitting formula and entropy weight of each influence index, a formula to predict the development height of the confined water rising zone is obtained:

$$H' = W_1H_a + W_2H_b + W_3H_c + W_4H_d$$
$$= 0.0964(0.0843M + 8.7225) + 0.1907(1.595P + 5.8787) + 0.3386(2.5226K + 7.5132) + 0.3743(20.434F + 5.9956)$$
$$= 0.0081M + 0.304P + 0.854K + 7.65F + 6.745 \quad (10)$$

Discussion

The SVR parameters obtained by the PSO optimization are: c is 13.7913; g $(1/\sigma^2)$ is 0.01; the termination generation is 100; the mean square error (MSE) of the test sample is 0.052728 and tends to be 0, which shows that the model has good generalization. The curve diagram of the fitting result of the confined water rising zone is shown in Fig. 4. The minimum relative error of the fitting results is 2.68%, the maximum relative error of the fitting results is 21.6%, and the average relative error is 11.83%. Thus, its fitting effect is preferable.

The predicted relative error of the zone of pressure water, which induces the height by using the multiple linear regression formula, was 2.61-49.2%, and the average relative error was 21.19%. The SVR was 6.65%-32.87%, and the average relative error was 16.5% (tab. 3). Compared with other methods, the predicted results of the Fuzzy-GRA-PSO-SVR model have good generalization and can be applied to field prediction.

***Table 3** Comparison of the relative error of each method*

test data	H/m	linear formula/m	relative error/%	Fuzzy-GRA-SVM/m	relative error/%	Fuzzy-GRA-PSO-SVR/m	relative error/%
21	17.9	16.46	8.04	16.64	7.04	16.2	9.5
22	17.6	17.14	2.61	16.43	6.65	16.73	4.94
23	33.1	21.92	33.78	24.35	26.44	26.34	20.42
24	21.3	18.68	12.3	23.32	9.48	21.87	2.68
25	8.7	12.98	49.2	11.56	32.87	10.58	21.6
average relative error			21.19		16.5		11.83

Conclusion

The higher correlative degrees among the aquifuge index, aquifer water pressure index, permeability index, structural index and original confined water rising zone are 0.8563, 0.9750, 0.9678 and 0.9614, respectively. The SVR parameters obtained by the PSO optimization are c=13.7913, g=0.01, CVmse=0.052728. The predicted relative error of the zone of pressure water inducing height using Fuzzy-GRA-PSO-SVR was 2.68-21.6%, and the average relative error was 11.83%. By comparing other methods, the predicted results of Fuzzy-GRA-PSO-SVR have good generalization and can be applied to field prediction.

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