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Research on Main Control Geological Factor Identification and Prediction Model of Coal Seam Gas Content

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Abstract: Coal seam gas content is a critical parameter for coal mine gas disaster prevention. To accurately determine the coal seam gas content, this study adopts the single-factor analysis method to investigate the geological factors influencing gas content in a specific coal mine. Three factors, namely bedrock burial depth, 50m-thickness influence coefficient of roof strata effect and coal seam thickness, are identified as the main controlling factors of gas content, with corresponding correlation coefficients of 0.6011, 0.3899 and 0.2527 respectively. Other factors including Cenozoic burial depth, effective gas-isolating thickness, moisture content and ash yield show relatively weak influences and are classified as secondary influencing factors. Subsequently, a nonlinear prediction model between coal seam gas content and its main controlling factors is established based on the support vector machine theory, and the gas content values are predicted. The research results demonstrate that the single-factor analysis method can effectively identify the main controlling factors of coal seam gas content, and the established support vector machine model can achieve high-precision prediction of gas content. The study outcomes can provide technical support for gas drainage and coal-gas outburst prevention in coal mines.

Keywords: Coal seam gas; Geological factor; Main controlling factor; Single-factor analysis method; Support vector machine.

1. Introduction

Coal seam gas content is one of the core parameters of coal seam gas, and it serves as a critical basis for predicting mine gas emission quantity and coal seam outburst risk [1-2]. Apart from the total amount of generated gas, the magnitude of coal seam gas content is primarily determined by the gas dissipation and migration conditions after coal formation, as well as the gas preservation capacity of coal. All these factors are ultimately governed by the geological conditions of coalfields and the occurrence conditions of coal seams. To achieve accurate determination of coal seam gas content, extensive research has been conducted by scholars worldwide. Cui Jianbin et al. analyzed the influences of coal seam burial depth, geological structures, folds, coal seam thickness and coal metamorphism on coal seam gas content, concluded that geological structures, coal seam burial depth and thickness are the main controlling factors of gas content in No.1 coal seam of Weijiadi Coal Mine, and obtained the predicted value of coal seam gas content through multiple linear regression analysis [3]. Zhou Xinlong et al. proposed an improved grey neural network prediction model for deep coal seam gas content based on grey entropy theory and RBF neural network theory [4]. Ma Lei et al. put forward a new gas content prediction model (GASA-BPNN model), which adopts the hybrid initialization of BP neural network (BPNN) using genetic algorithm (GA) and simulated annealing algorithm (SA) [5]. Huang Chunxiang et al. established a coal seam gas prediction model based on LM-BP neural network, used relevant parameters of geological exploration boreholes to construct samples for model training and prediction, and compared the performance of the designed prediction model with that of the BP neural network model [6]. The results show that the two models are basically consistent in prediction accuracy, both exceeding 90%. Wang Lin et al. obtained 7 gas content prediction models through base model integration, and finally selected four optimal models: Stacking-LSSVM-Adaboost, Adaboost,Stacking-Adaboost-DBNandStacking-LSSVM-Adaboost-DBN[7]. Existing studies have proven that in most cases, the relationship between coal seam gas content and its influencing factors presents strong nonlinear complexity. Based on the above analysis, this paper first identifies the main controlling factors of gas content, then constructs a nonlinear mapping relationship between gas content and its key influencing factors using the support vector machine method, which provides a new technical idea for the research of coal seam gas content prediction.

2. Analysis of main controlling factors of gas content

From view of gas geology, coal seam gas content is related to the amount of gas generated, in addition, it is mainly depends on the dissipation and migration conditions of gas after coal generated as well as the ability of coal to save gas. All of the above depend on coalfield geological conditions and occurrence condition of coal seams. Factors affecting coal seam gas content include geological structure, coalfield geological history, embedding depth of coal seam, degree of coal metamorphism, coal seam outcrop, coal bed surrounding rock properties, hydrogeology condition,etc.. At present, 45 pairs of data of gas content, buried depth and coal quality of a coal mine were collected. 50m influence coefficient refers to the thickness influence coefficient of roof rock effect, what is specifically shown in Table 1.

When analyzing macroscopic control factors of coal seam gas content, the single factor method is used to analyze geological factors of coal mine gas content respectively. For buried depth, the relationship between bedrock and cenozoic buried depth with gas content have to be analyzed.

Bedrock buried depth linear fitting: y=0.0137X+2.7633, correlation coefficient: R2=0.6011. The results are shown in Fig.1.

Table 1. Gas content controlling factors of a coal mine

Sample	Geological factors									Gas (m3/t)
	Buried depth			Surrounding rock			Coal quality			
	Depth (m)	Bedrock depth(m)	Cenozoic buried depth(m)	Effective trapping thickness (m)	50m sandstone ratio (%)	50m influence coefficient	Coal thickness (m)	Moisture (%)	Ash (%)	
1	388	120.1	267.9	0	0.61	0.934	2.4	0.86	12.05	4.95
2	632.1	624.19	7.91	0	0.17	1.133	7.6	0.92	14.00	11.6
3	455.4	437.9	17.5	1.32	0.32	1.32	5.89	0.81	11.53	6.52
4	805	731.9	73.1	0.731	0.24	1.067	9.7	1.46	10.71	10.83
5	248.9	226	22.9	0	0.59	0.792	3.2	1.3	16.14	5.1
6	699.5	476.8	222.7	0.343	0.39	0.368	7.94	0.34	14.28	9.75
7	468.5	461	7.5	1.33	0.29	0.891	4.9	1.15	9.98	6.89
8	228.2	226.7	1.5	0	0.33	1.086	1.9	0.86	14.50	6.08
9	472	462	10	0.2	0.12	0.945	2.9	1.15	13.25	10.96
10	326.8	309.4	17.4	0.429	0.32	1.45	5	1.26	14.40	7.65
11	302.9	291.9	11	0	0.31	0.3	4	0.93	16.63	7.9
12	348.3	150.2	198.1	1.5	0.25	1.1	6.2	0.92	14.20	8.3
13	342.6	180.3	162.3	0.45	0.35	0.45	6.5	0.83	15.80	5.46
14	388	372	16	2.3	0.23	0.98	6.41	0.81	12.14	8.11
15	346	278	68	1.32	0.56	0.85	5.28	0.67	13.26	5.36
16	703	625	78	2.6	0.21	1.46	9.2	0.32	10.50	14.13
17	524	392	132	3.2	0.49	0.6	4.8	0.61	14.30	6.55
18	673	581	92	2.5	0.14	1.51	4.1	0.28	12.60	10.27
19	692	392	300	1.6	0.32	1.23	5.6	0.29	12.50	7
20	381	325	56	2.41	0.40	1.13	3.46	1.41	17.20	8.97
21	267	232	35	3.5	0.38	0.76	5.17	1.52	11.89	7.70
22	354	272	82	2.6	0.41	1.03	5.2	0.82	13.50	8.83
23	278	178	100	0.65	0.56	0.46	2.5	1.32	22.30	3.21
24	317	231	86	1.2	0.53	0.52	3.2	1.31	18.60	4.64
25	397	352	45	0.32	0.42	0.96	2.86	1.35	15.60	7.76
26	385	380	5	3.1	0.36	1.17	3.45	1.3	23.10	9.92
27	389	374	15	0.54	0.31	1.06	3.5	1.28	21.30	7.48
28	431	386	45	0.92	0.35	0.99	3.78	1.15	14.20	7.96
29	395	374	21	0.2	0.25	1.1	4	1.4	20.30	8.21
30	214	132	82	1.62	0.12	1.23	4.1	1.23	16.20	6.9
31	299	221	78	1.12	0.28	1.18	5.1	1.16	16.70	8.53
32	284	232	52	1.17	0.17	1.21	5.97	1.15	15.80	7.89
33	341	246	95	0.86	0.21	1.18	3.62	1.14	12.60	6.54
34	369	346	23	1.82	0.27	1.2	4.32	1.18	14.90	6.86
35	417	391	26	2.1	0.31	0.91	4.8	0.98	15.20	9.68
36	213	142	71	1.51	0.62	0.36	2.32	0.95	13.00	2.45
37	239	182	57	1.2	0.23	0.45	3.2	1.2	10.84	3.42
38	321	200	121	2.3	0.36	0.51	5.6	1.61	10.82	3.38
39	324	221	103	2.1	0.21	0.63	5.72	1.52	10.28	4.23
40	350	256	94	2.68	0.35	0.79	6.37	0.56	9.82	6.46
41	357	227	130	3	0.28	0.62	6	0.62	11.51	5.13
42	184	138	46	0.78	0.64	0.52	4.36	1.12	16.70	3.34
43	252	176	76	0.5	0.65	0.47	2.6	1.1	17.20	2.9
44	281	200	81	0.92	0.59	0.65	2.52	0.98	14.30	5.98
45	334	302	32	1.1	0.21	0.85	4.2	0.52	13.20	5.5

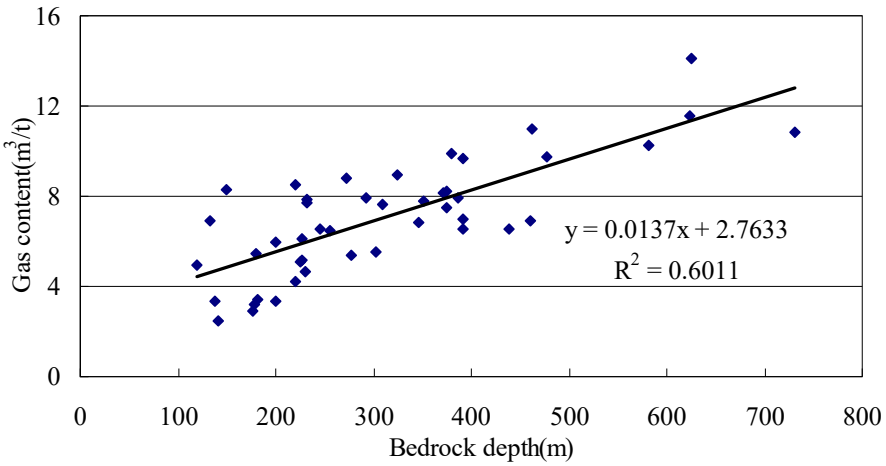

Fig.1 Relationship between bedrock buried depth and gas content

The analysis results of the other factors are shown in Table 2.

Table 2. The single factor analysis results of geological factors on gas content

Geological factors		Fitting results	R2	Result
Buried depth	Buried depth(m)	y=0.0119x+2.4346	0.4703	
	Bedrock buried depth(m)	y=0.0137x+2.7633	0.6011	Max
	Cenozoic buried depth(m)	y=-0.006x+7.4996	0.0261	
Surrounding rock	Effective trapping thickness(m)	y=0.2989x+6.6519	0.0138	
	50m sandstone ratio(%)	y=-9.7128x+10.442	0.3249	
	50m influence coefficient	y=4.8622x+2.6848	0.3899	Max
Coal quality	Coal thickness(m)	y=0.7144x+3.6942	0.2527	Max
	Moisture content(%)	y=-1.6275x+8.7017	0.0503	
	Ash content(%)	y=-0.0285x+7.4625	0.0013	

According to Table2, it can be seen that coal seam bedrock buried depth is the most important geological factor, followed by surrounding rock. The impact of influence coefficient and sand content rate are the most significant in surrounding rock. And coal depth also has some impact on coal seam gas content. In addition, the impact of cenozoic depth, coal quality on gas content are relatively smaller, which as a result will not be regarded as the main factors affecting coal gas content.

3. Multivariable prediction of the gas content

3.1. Multivariate modeling of the gas content

Through the single factor analysis above, the factors closely link to the content of the coal seam methane in this mine is determined. According to the level of the influence significance, devide it successively as the bedrock buried depth, 50m influence coefficient and coal thickness, consider the three factors as the main factors that influence the content of the coal seam methane. Choose them as independent variables, gas content as dependent variable, then mathematic relation between them can be established. Since the complexity, dynamics,nonlinearity and random uncertainty of coal seam gas content system, its prediction model must develop toward the direction of nonlinearity and multiparameter constantly. Therefore the paper chooses the model of support vector machine to build the quantitative relation between them.

SVM is a kind of machine learning algorithm brought up by Vapnik from the AT&T Bell laboratory and his study team in 1995. Its specific algorithm can refer to the literature[7].According to the basic idea mentioned above, we take advantage of SVM toolkit developed by Steve Gunn, and then the regression analysis and prediction of the coal seam methane content can be achieved with the help of the simulation software Matlab. Since various different feature spaces can result in different kernel function, so it will has a relatively wide range of chooses. The main kernel functions provided by the SVM toolkit are multinomial kernel,index basic kernel in radial direction,kernel of multilayer perception and the spline kernel, etc.

The procedures of the prediction model of coal seam gas content based on the SVM are as follows:

(1) Gather information, and determine the main factors that influence coal seam methane content;

(2) Analysis the data, screening samples, structure the sample sets and then conduct normalization to the sample data. It is needed to eliminate the influence of each factor due to the difference of its dimensions and unit, thus to make sure that the values normalized can be in the interval [0,1];

(3) Solve the model and choose appropriate kernel function and parameters. Call the related function in the SVM toolkit combined with the data in the sample sets, and then realize the algorithm with the programme in the Matlab software;

(4) Input the related index values that influence the gas content and need to be predicted to the model that has been practiced well, and then output the prediction values of the gas content.

3.2. Prediction of the gas content

According to the SVM theory, combining with the 45 reliable gas content points measured actually and based on the geology element data in Table1, then analysis the gas content with the SVM model. The prediction process is as follows: firstly, choose the sample data of the former 40 groups to proceed the model training which takes only 0.1s in every training, and then determine the best training parameter after the repetition test. Define the punish coefficient C as 1000,

the deviation e as 0.005, and choose 'erbf ' as the kernel function. Then the gas content in the later 5 groups. The result can be shown in Fig.2 and Table 3. From Fig.2 and Table3, the fitting degree of the prediction result is high compared with the actual measured values. So it can be used to measure the actual gas content.

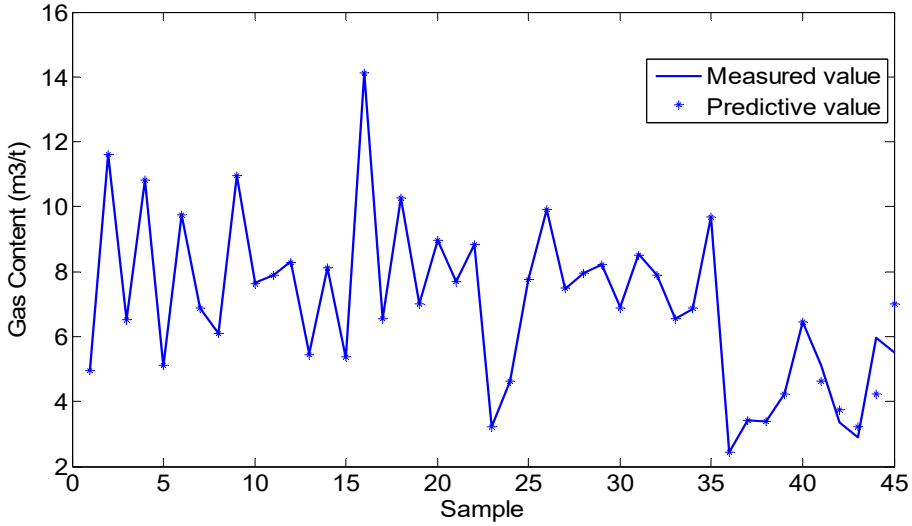

Fig.2 Prediction of gas content with the SVM model

Table 3. Result of the SVM prediction

Sample number	41	42	43	44	45
Actual gas value(m3/t)	5.13	3.34	2.9	5.98	5.5
Predicted gas value(m3/t)	4.71	3.76	3.23	4.33	6.8
Rresidual error	0.42	-0.42	-0.33	1.65	-1.3

4. Conclusions

(1) The influencing factor of coal seam gas content in a certain coal is researched with the single-factor method. Then the bedrock depth, 50m influence coefficient and coal thickness are determined as the main control factors. And the corresponding related coefficient are 0.6011, 0.3899, 0.2527. However, the related coefficient of the following factors are relatively small, which is the cenozoic buried depth, effective trapping thickness, moisture and ash content, etc.

(2) The nonlinearity model between the coal seam gas content and the main control factors is established with the SVM theory, and the gas content is also predicted. The fitting degree of the prediction result is high compared with the actual measured values. So it can be used to measure the actual gas content.

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