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Application of BP neural network model in productivity prediction and evaluation of CBM wells fracturing

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Abstract. The geological conditions of coal-bed methane (CBM) are complex in China, so it is difficult to predict the production of CBM wells. Methodology of artificial intelligence was introduced in the mining of CBM. According to the characteristics of target block reservoir, the gray correlation analysis technology is used for analyzing the degree of correlation between each parameter and CBM production. And then the BP artificial neural network model is used in prediction and evaluation of CBM wells fracturing production. Application results show that the method improves the prediction and evaluation accuracy of CBM production.

1. Introduction

The geological conditions and the mining process of CBM is complex in China, and the types of reservoir are diversiform. So, it is difficult to predict the production of CBM wells. In order to increase production, we must using hydraulic fracturing to stimulate the coal-bed methane reservoir. Meanwhile, the optimizing fracturing construction can be guided only by the accuracy of production prediction.

Methodology of artificial intelligence was introduced in the petroleum engineering. Zhou et al[1] tried to use the fuzzy neural network method to identify the type of reservoir , Zhang et al [2] used neural network to predict permeability values, Wang and Zhang [3] used neural network model to identify the lithology by log data, Gao et al [4] identified water/oil/gas layer through the construction of self-organizing map network, Karimpouli [5] used a committee with supervised machine to predict the permeability. Fernandes[6] used multiple neural network model and the empirical formula to identify oil and gas layer. Bravo et al[7] summarized the state of Artificial Intelligence in the exploration and development.

Intelligent method is also widely used in the development of CBM. Wu et al[8] applied neural network technology to evaluate the parameters of coal reservoir, Hou et al [9] used the BP neural network methods to interpret the log data of CBM quantitatively. Du et al [10] built BP neural network model which is based on time series prediction ideas and suitable for coal-bed gas well productivity prediction. Ma et al[11] proposed a method to forecasting the production, which is based on the BP neural network of the principal component. These methods have achieved good effect. Therefore, the gray correlation degree is used to select parameters, and then BP neural network is used to predict the deliverability of target block, finally we also have analyzed the effect of application.

2. Mathematical Model

2.1 Gray Correlation Analysis

Grey correlation analysis is an effective method on selecting parameters in CBM fracturing. First of all, potential development index and its corresponding influence parameters are identified based on CBM development background. Secondly, the degree of correlation between development index and its corresponding influence parameters are calculated. Finally, the main influence parameters of each development index accorded on the degree of correlation are determined. And the main influence parameters are used to predict the effect of CBM fracturing.

Set the pre-processed data is x_i, the recording data is x_j, the gray correlation coefficient is $\zeta_{ij}(k)$. k is the sampling point which is the correlation between x_i and x_j. The sum of sampling points is n. The expression of gray correlation coefficient is:

$$\xi_{ij}(k) = \frac{\alpha_{\min} + \alpha_{\max} * \rho}{\alpha_{ij}(k) + \alpha_{\max} * \rho} \qquad (k = 1, 2, \ldots\ldots, n)$$

Where $\alpha_{ij}(k) = \left| x_i(k) - x_j(k) \right|$, $\alpha_{\min} = \min\limits_j \min\limits_k \alpha_{ij}(k)$ and $\alpha_{\max} = \max\limits_j \max\limits_k \alpha_{ij}(k)$, ρ is a constant which is between 0 and 1 and generally taken as 0.5.

So, set the correlation degree γ_{ij}:

$$\gamma_{ij} = \frac{1}{n} \sum_{k=1}^{n} \xi_{ij}(k)$$

γ_{ij} reflects the correlation degree between data x_i and x_j and describes the relative changes between data x_i and x_j during system development process.

The parameters which have impacted the effect of CBM fracturing can be analyzed from the initial parameters by using the order of the correlation degree. Besides, it will lay a foundation for the CBM fracturing effect prediction technology by achieving the influence degree of various parameters on CBM fracturing.

2.2 BP Neural Network

Artificial neural network is a kind of mathematical model which imitates the characteristics of animal neural network behavior and runs the algorithm of distributed parallel information processing. It achieves the purpose of processing information by adjusting the connected relationship among the internal and a large number of nodes. In this paper, the model consists of input layer, double hidden layers and output layer. Using unipolar Sigmoid function describes the non-linear relationship between output layer and input layer of each neuron's. Namely:

$$f(x) = \frac{1}{1 + \exp(-x)}$$

The relationship between every output O_{pi}^{l} and every input $O_{pj}^{(l-1)}$ of universal layer can be expressed as the following:

$$O_{pi}^{l} = f_s \left[I_{pi}^{(l)} \right]$$

Where $$I_{pi}^{(l)} = \sum_{j=0}^{L-1} w_{ij}^{(l)} O_{pj}^{(l-1)} \qquad i = 0, 1, \cdots Q-1$$

In reverse learning of network weights, gradient steepest descent algorithm is used. Correction calculation of network weights is completed as following:

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$$\Delta_p w_{ij}^{(l)} = -\alpha \frac{\partial E_p}{\partial w_{ij}^{(l)}}$$

All inputs are normalized by equation (1) before training.

$$\bar{x} = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{1}$$

3. Numerical Simulation

3.1 Gray Correlation Analysis Steps and Result

(1) calculate the degree of correlation between development index and its corresponding influence parameters;

(2) order influence parameters by their degree;

(3) choose influence parameters of development index based on the result of step two.

20 layers' data of fracturing, logging and mining in Guizhou block is analyzed by the grey correlation analysis method. All of the influence parameters are included in table 1, and the result of selecting is shown in table 2.

Table 1. Influence parameters

Types	Parameters
Logging	Compensated density, Compensated neutron, Well diameter, Microsphere focused resistivity, Deep lateral resistivity, Shallow lateral resistivity, Natural potential, Natural gamma-ray, Interval transit time, Position, Coal-seam depth, Coal-seam thickness, 12 parameters
Fracturing	Perforation thickness, Operation discharge, Pad fluid volume, Sand-carrier fluid volume, Total liquid volume, Sand volume, The average sand ratio, Fracturing fluid types, Proppant types, Fracture pressure, Construction pressure, 30min pressure drop, 12 parameters
Mining	Intensity of mining, Dynamic fluid level, Interval time between fracturing and mining, Bottom hole flowing pressure, Casing pressure, Accumulation time of producing gas, 6 parameters

Table 2. Result of parameter optimization of Guizhou block based on grey correlation analysis

Parameters	Well depth	Perforation thickness	Dynamic fluid level	Interval time between fracturing and mining	Bottom hole flowing pressure
Degree of correlation	0.4323	0.6757	0.701	0.7603	0.1542
Order	13	5	4	2	19
Parameters	Compensated density	Well diameter	Deep lateral resistivity	Shallow lateral resistivity	Natural gamma-ray
Degree of correlation	0.3706	0.5516	0.2076	0.773	0.3432
Order	15	9	18	1	16
Parameters	Natural potential	Pad fluid volume	Total liquid volume	Sand volume	Casing pressure
Degree of correlation	0.6981	0.6032	0.5956	0.5505	0.6266
Order	3	7	8	10	6
Parameters	Average discharge	Interval transit time	Compensated neutrons	Water yield	
Degree of correlation	0.434	0.4222	0.5186	0.2139	
Order	12	14	11	17	

From the table, we can find out that the degree of correlation between mining parameters and gas production, the degree of correlation between geological parameters and gas production are both very high. On the contrary, the influence of partial fracturing parameters is relatively low. But, considering the integrity of the fracturing parameters, fracturing parameters doesn't have been filtered out. Therefore, 19 parameters have been selected at last, including well depth, perforation thickness, dynamic fluid level, interval time between fracturing and mining, bottom hole flowing pressure, compensated density, well diameter, deep lateral resistivity, shallow lateral resistivity, natural gamma-ray, natural potential, pad fluid volume, total liquid volume, sand volume, casing pressure, average discharge, interval transit time, compensated neutrons, water yield.

3.2 Neural Network Prediction Effect

A neural network model of CBM fracturing effect prediction is established for the target block according to the result of parameter selection. It consists of input layer, double hidden layers and output layer, as shown in Figure 1.

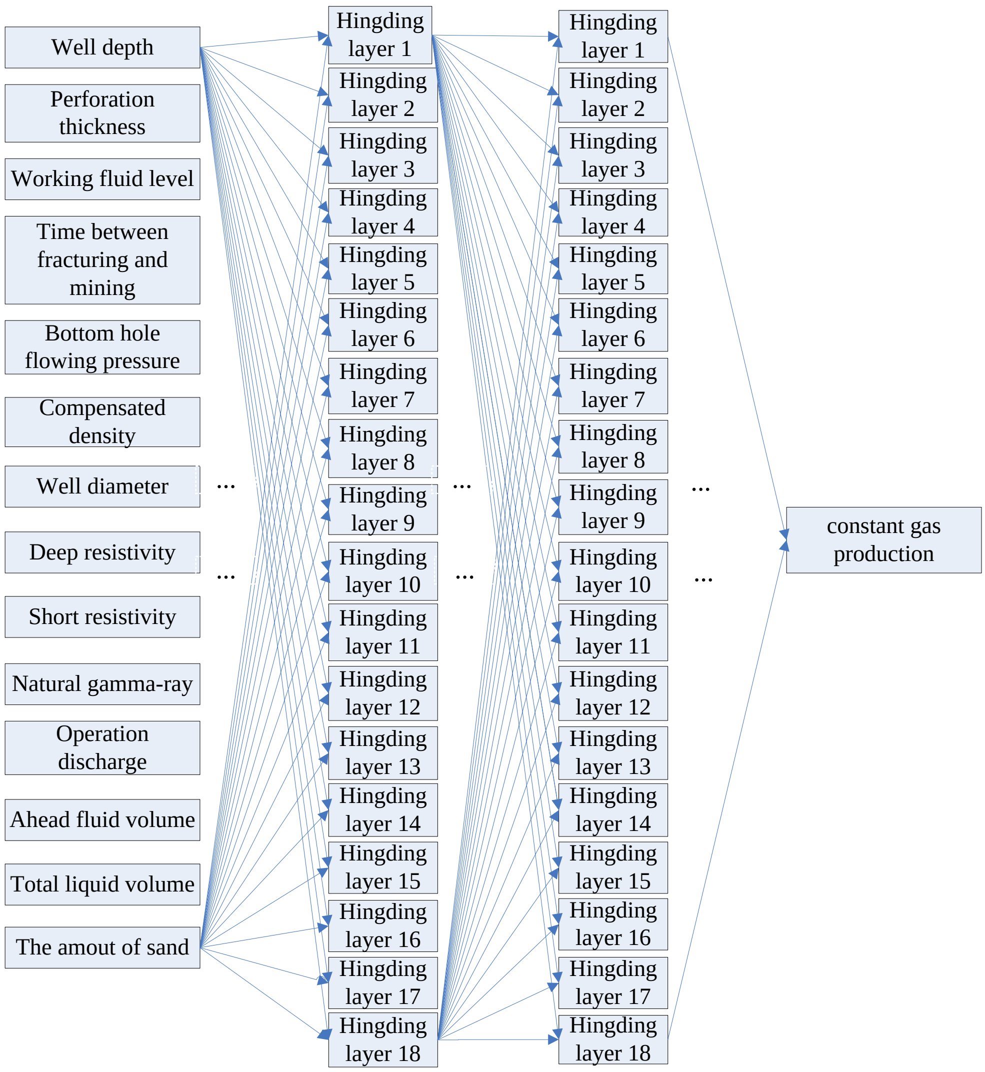

Figure 1. The neural network model for predicting the production of CBM

According to the result of parameter selection, there are 19 inputs and only 1 output in this neural network model. In the light of the neural network theory, the number of hidden layer nodes during 8 to 20 is reasonable. And a repeated trial shows that the number of hidden layer nodes selected as 18 is the best result. As a consequence, our prediction model scale is 14×18×18×1. The data of target block is

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trained by using the prediction model. The network weights of three layers are fitted out by using 80 samples.

3.2.1 Fitting Result. After the fitting for 80 samples, the average relative error of gas production rate is 0.76%, the accuracy is 99.24%. The fitting result is shown in table 3.

Table 3. The fitting result for 80 layers (partial data)

Well number	Level number	Actual production (m^3/d)	Fitting production (m^3/d)	Relative error (%)
GZ-1	3#	53.72	54.08	0.67%
	15#	76.28	76.59	0.41%
GZ-2	3#	104.81	105.15	0.32%
	15#	75.19	76.26	1.42%
GZ-3	3#	28.24	28.09	0.53%
	15#	31.76	31.28	1.51%
GZ-4	3#	57.3	56.96	0.59%
	15#	62.7	62.32	0.61%
…	…	…	…	…
Average error (%)		0.76%		

3.2.2 Prediction Result. Using the rest 5 layers' data of the target blocks to predict fracturing production and compare with actual gas production, the average relative error is 15.56%, it means that the accuracy is 84.44%. For the field construction, the prediction accuracy is fully able to meet the requirements. The results are shown in table 4 and Figure 2.

Table 4. Prediction results of 5 layers

Well number	Level number	Actual production (m^3/d)	Prediction production (m^3/d)	Relative error (%)
GZ-01	3#	482.18	393.19	18.46%
	15#	537.82	488.81	9.11%
GZ-02	3#	27.82	32.532	16.94%
	15#	62.18	74.79	20.28%
GZ-03	3#	123.43	139.5	13.02%
Average error (%)		15.56%		

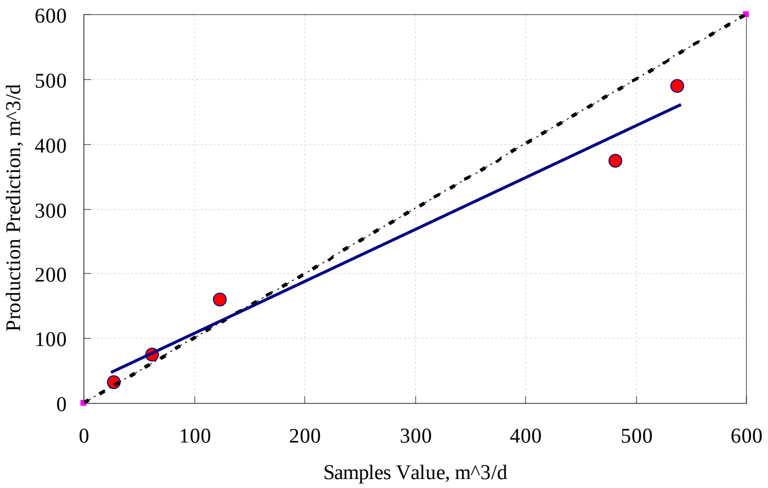

Figure 2. BP neural network performances

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4 Conclusions

(1) According to the characteristics of target block reservoir, the gray correlation analysis is introduced to select the influence parameters of CBM fracturing. As a result, the selected 19 parameters are almost as the same as the real situation of construction site.

(2) The neural network theory is introduced to build the effect prediction model of CBM fracturing. After the fitting for 80 samples, the average relative error of gas production is 0.76%, the accuracy is 99.24%. Besides, using the rest 5 layers' data to predict gas production, the average relative error is 15.56%, it means that the accuracy is 84.44%. For the field construction, the prediction accuracy is fully able to meet the requirements.

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