Application of a neural network system combined with genetic algorithm to rank coalbed methane reservoirs in the order of exploitation priority

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Abstract: A new method based on the combination of a neural network and a genetic algorithm was proposed to rank the order of exploitation priority of coalbed methane reservoirs. The neural network was used to acquire the weights of reservoir parameters through sample training and genetic algorithm was used to optimize the initial connection weights of nerve cells in case the neural network fell into a local minimum. Additionally, subordinate functions of each parameter were established to normalize the actual values of parameters of coalbed methane reservoirs in the range between zero and unity. Eventually, evaluation values of all coalbed methane reservoirs could be obtained by using the comprehensive evaluation method, which is the basis to rank the coalbed methane reservoirs in the order of exploitation priority. The greater the evaluation value, the higher the exploitation priority. The ranking method was verified in this paper by ten exploited coalbed methane reservoirs in China. The evaluation results are in agreement with the actual exploitation cases. The method can ensure the truthfulness and credibility of the weights of parameters and avoid the subjectivity caused by experts. Furthermore, the probability of falling into local minima is reduced, because genetic the algorithm is used to optimize the neural network system.

Key words: Coalbed methane, neural network system, genetic algorithm, evaluation index, weight

1 Introduction

Proper exploitation and utilization of coalbed methane are of great significance in safe production of coal mines, relieving the shortage of conventional energy and protecting the environment. In China, the coalbed methane reservoirs are abundant, but many coalbed methane reservoirs remain unexploited. Part of the unexploited coalbed methane reservoirs are not fit for exploitation technically and economically, so, it is necessary to rank the exploitation priority of all unexploited coalbed methane reservoirs and select the good ones, which can provide the direction for the exploitation of coalbed methane reservoirs and avoid the enormous economic loss resulting from wrong decision (Zhang and Xie, 2002).

It is known that some parameters of coalbed methane reservoirs are very important to the exploitation result. The key of ranking is to acquire the weights of these sensitive parameters. Traditionally, these weights are obtained by scoring by experts, which inevitably have randomization and subjectivity. In this paper, the combination of a neural network and a genetic algorithm is applied for the first time to acquire the weights of sensitive parameters. The neural network is used to acquire the weights through training samples and the genetic algorithm is used to optimize the

joint weights of neurons in case neural network falls into local minimum. Test result shows that the comprehensive evaluation method established in this paper is advanced and practical.

2 Neural network and genetic algorithm comprehensive evaluation method

2.1 Triple-layer back propagation neural network

Artificial neural network (ANN) is a physical cellular system, which can acquire, store, and utilize empirical knowledge. Especially the triple-layer back propagation (BP) neural network is currently the most popular model of ANN. This model contains not only input nodes and output nodes, but also multi-layer or mono-layer hidden nodes. Fig. 1 is a construction chart of a triple-layer BP neural network.

The artificial neuron network is a black box, which includes the weights modifying process from the output layer to the input layer. The calculation process of an artificial neuron network can be divided into two steps. In the first step, the information is input from input layer and the output values of each hidden layer are calculated. In the second step, the output errors of each hidden layer are calculated from back to front, at the same time, the errors are used to modify the weight of the prior layer and the error will gradually decrease. Through training with a lot of samples, the optimum weights can be obtained.

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Fig. 1 Structure of triple-layer BP network

There are I neurons in the input layer, J neurons in the hidden layer and K neurons in the output layer. In general, sigmoid functions are convenient for searching and solving by the gradient technique, so they are usually chosen as the activation function for output layer and hidden layer nodes. Eq. (1) is a typical sigmoid function.

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

Given input nodes O_i , the values of hidden node M_j and output N_k can be calculated, based on the joint weights, w_{jn} and v_{kn} (Yu and Chen, 1997):

$$M_j = f \left(\sum_{n=1}^I w_{jn} \bullet O_n \right) \quad (2)$$

$$N_k = f \left(\sum_{n=1}^J v_{kn} \bullet M_n \right) \quad (3)$$

The joint weights should be revised many times during the progress of the error propagating back in BP networks. The variation of joint weights each time is solved by the method of gradient descent. Because there is no objective output in the hidden layer, the variation of joint weights in the hidden layer is solved with the help of error back propagation in the output layer.

The variation of joint weights can be calculated with the following equation:

$$\begin{cases} \Delta w_{ij} = -\eta \frac{\partial E}{\partial w_{ij}} \\ \Delta v_{jk} = -\eta \frac{\partial E}{\partial v_{jk}} \end{cases} \quad (4)$$

where η is the learning efficiency.

The error function is as follows:

$$E = \sum_{k=1}^K (N_k - D_k)^2 / 2 \quad (5)$$

E is a nonlinear function of the sigmoid function. D_k is the desired output values of the neuron network. So, in the space of joint weights constructed by E , many local minimum points exist. Traditionally, the method of gradient descent is adopted to train the network, in which weights are given randomly before the beginning of training, so the network is likely to be trapped into a point of local minimum.

2.2 Genetic algorithm introduction

Genetic algorithm is based on a biological metaphor, which views learning as a competition among a population of evolving candidate problem solutions. Conventionally, the genetic algorithm contains a selection operator, crossover operator and mutation operator. A “fitness” function evaluates each solution to decide whether it will contribute to the next generation of solutions. Then, through operations analogous to gene transfer in sexual reproduction, the algorithm creates a new population of candidate solutions. In order to use the genetic algorithm, a solution must be presented to the problem as a genome (or chromosome). The genetic algorithm then creates a population of solutions and applies genetic operators, such as mutation and crossover to evolve the solutions in order to find the best one(s).

2.3 Combination of BP neural network and genetic algorithm

The idea that combining genetic algorithm and BP algorithm to train the neural network is depicted as the following: Firstly, utilize the genetic algorithm to optimize original weights and chose a preferable search space in the solution space, then, utilize the BP algorithm to find an optimum solution in the preferable search space. By this method, the risk of falling into a local minimum can be averted. At the same time, the convergence rate will be obviously enhanced.

The joint weights in the triple-layer BP neural network contain w_{jn} and v_{kn} , in which w_{jn} is the joint weight between input layer joint and hidden layer joint, while v_{kn} is the joint weight between hidden layer joint and output layer joint. The object that the genetic algorithm treats is a one dimensional variable, while w_{jn} and v_{kn} are all two dimensional vectors. So, before using the genetic algorithm, w_{jn} and v_{kn} should be changed into one dimensional variable and renumbered. The conversion process can be achieved by using the following equation (Liu and Li, 2003).

$$\begin{cases} v_j = v_{jk} & j = 1, 2, \dots, J \\ v_{I(j-1)+i} = w_{ij} & j = 1, 2, \dots, J; i = 1, 2, \dots, I \end{cases} \quad (6)$$

The total amount of renumbered joint weights is $N=J+IJ$. In genetic algorithm, every joint weight is regarded as a chromosome and all weights are joined as the genome of the

neural network.

In the comprehensive evaluation method, the reciprocal value of neural network error's root-mean-square is taken as the fitness function of genetic algorithm, which can be written as follows (Yang et al, 2001a):

$$f(w) = 1.0 / \sqrt{\sum \left(\frac{N-D}{M} \right)^2} \quad (7)$$

where N is the actual output vector; D is the objective vector; and M is the number of samples.

2.4 Application procedure of the comprehensive evaluation method

The procedure of applying the genetic algorithm and the BP neural network comprehensive evaluation method is depicted as follows.

- 1) Setting the structure of neural network; giving the numbers of input nodes, output nodes and hidden nodes; and installing the convergent accuracy.
- 2) Giving the involved parameters of genetic algorithm, such as selection operator, crossover operator, mutation operator and population rule.
- 3) Initializing the population.
- 4) Executing the genetic algorithm to optimize the joint weights of BP neural network globally.
- 5) Executing BP neural network to search the global minimum based on the optimized weights, which are obtained by genetic algorithm. If the error of neural network is less than ε , execution will stop, if not, return to Step 4) until it reaches the preset precision.

3 Optimization model for coalbed methane reservoirs

3.1 Selection and normalization of sensitive parameters

When selecting the sensitive parameters of coalbed methane reservoirs, two aspects should be considered. Firstly, the parameters have significant impact on the exploitation result of coalbed methane reservoirs. Secondly, the parameters should be easily acquired. Based on the two considerations, the following parameters are selected: permeability, porosity, gas content, gas saturation, reservoir thickness, burial depth, reservoir pressure, hydrogeologic appraisal and adsorbability (Hu et al, 2003; Lian et al, 2005; Lu, 2007; Yang et al, 2001b). The values of the parameters here used are the average values for each coalbed methane reservoir.

3.2 Establishment of combined comprehensive evaluation method

In this paper, the triple-layer BP neural network is selected to train the samples and acquire the weights of sensitive parameters. The nine selected sensitive parameters are regarded as the input nodes and the ultimate recovery as

the only output node. For the hidden layer, eight nodes are chosen according to tests. Genetic algorithm is introduced to optimize the joint weights in real time. The structure of the comprehensive evaluation model is shown as Fig. 2.

Fig. 2 Structure of comprehensive evaluation model

When using triple-layer BP neural network, it is important to select and train samples. The coalbed methane reservoirs which have been successfully exploited abroad mostly are in medium- or low-rank coal, but in China, the coalbed methane reservoirs which have been successfully exploited mostly are in high-rank coal (Wang et al, 2005). In order to make the comprehensive evaluation model established in this paper more scientific and adaptable, different coal ranks were considered and about 80 samples were selected as training samples. The samples selected are distributed as follows: high-rank coal blocks mainly in the south of the Qinshui Basin in China and the Raton Basin in the USA; medium-rank coal blocks mainly in the Daning-Hancheng area in China and the Mannville Basin in the north of Alberta province in Canada; low-rank coal blocks mainly in the Tiefu, Fuxin, Tuha, and Junggar basins in China and the Black Warrior, Powder River, San Juan, and the Uinta basins in the USA.

3.3 Sample training and acquisition of weights

When the total errors are less than ε , the weight of each parameter can be obtained with the following equation (Zurada, 1992):

$$Y_i = \frac{\sum_{h=1}^J [||WIH_{i,h}|| / \sum_{i=1}^I |WIH_{h,i}|] \cdot \sum_{O=1}^K |WHO_{h,o}|}{\sum_{i=1}^I [\sum_{h=1}^J [||WIH_{i,h}|| / \sum_{i=1}^I |WIH_{h,i}|] \cdot \sum_{O=1}^K |WHO_{h,o}|]} \quad (8)$$

where $WIH_{i,k}$ is the joint weight from input node i to hidden node k , $WHO_{k,o}$ is the joint weight from hidden node k to output node o . I , J , and K are the numbers of input nodes, hidden nodes and output nodes, respectively.

The weights of sensitive parameters acquired from the comprehensive evaluation model are shown in Table 1.

Table 1 Weights of sensitive parameters

Porosity	Permeability	Adsorbability	Gas saturation	Burial depth	Gas content	Reservoir thickness	Reservoir pressure	Hydrogeologic appraisal
0.07	0.173	0.161	0.14	0.088	0.193	0.053	0.088	0.035

3.4 Normalization of sensitive parameters

In order to conveniently compare and analyze the values of different parameters of several coalbed methane reservoirs, the subordinate functions for the nine sensitive parameters were established, which can normalize the actual values of parameters in the range between zero and unity (Hu et al, 2003; Lian et al, 2005; Lu, 2007; Yang et al, 2001b).

1) Subordinate functions for permeability, porosity, gas content, gas saturation and reservoir pressure

The permeability and porosity of the coalbed methane reservoir are controlled by many factors, such as the composition of coal, fracture geometry parameter, and earth stress. The permeability and porosity also influence the exploitation result of coalbed methane reservoirs. The greater the permeability and porosity, the better the exploitation result.

Gas content and gas saturation are the key parameters which influence the abundance of coalbed methane resources. The greater the values of these two parameters, the better the exploitation result.

Reservoir pressure is an indicator of reservoir energy. The higher the reservoir pressure, the more favorable the exploitation (Zhang, 2007)

So, Eq. (9) can be used as the subordinate function for these five parameters:

$$y_{ij} = \frac{x_{ij}}{\max_{1 \leq j \leq n}(x_{ij})} \quad (9)$$

where x_{ij} is the value of parameter i in the coalbed methane reservoir j ; $\max(x_{ij})$ is the maximal value of parameter i for all of the coalbed methane reservoirs; and n is the total number of the coalbed methane reservoirs.

2) Subordinate function for coalbed methane reservoir thickness

The greater the reservoir thickness, the more effective the exploitation, but this effect will not be so significant when the thickness of the coalbed methane reservoir is beyond a specific value. So, the normal curve can be used to describe the subordinate function of reservoir thickness:

$$y_{chh_j} = \begin{cases} 0 & x_j \leq 3 \\ 1 - \exp\left(-\frac{x_j - 3}{8.71}\right)^2 & x_j > 3 \end{cases} \quad (10)$$

3) Subordinate function for midpoint of burial depth

The deeper the coalbed methane reservoir, the more difficult the exploitation. So, the mountain shape curve can be

used as the subordinate function of burial depth:

$$y_{sh} = \begin{cases} 1 & x < 600 \\ \frac{1}{2} - \frac{1}{2} \sin \frac{\pi}{200}(x - 800) & 600 \leq x < 1000 \\ 0 & x \geq 1000 \end{cases} \quad (11)$$

4) Subordinate functions for absorbability and hydrogeologic appraisal

These two parameters are qualitative variables. Eqs. (12) and (13) can quantify them respectively.

$$y_i = \begin{cases} 1 & \text{good} \\ 0.5 & \text{medium} \\ 0 & \text{bad} \end{cases} \quad (12)$$

$$y_j = \begin{cases} 1 & \text{good} \\ 0.5 & \text{medium} \\ 0 & \text{bad} \end{cases} \quad (13)$$

3.5 Arrangement of exploitation priority

By using the comprehensive evaluation model established in this paper, the weights of sensitive parameters Y_i can be obtained. The actual values of parameters of coalbed methane reservoirs can be normalized with the subordinate functions (Eqs. (9)-(13)) to y_i . Then, the comprehensive evaluation value of coalbed methane reservoirs can be obtained from Eq. (14).

$$P_i = \sum Y_i \cdot y_i \quad (14)$$

Based on the evaluation values of different coalbed methane reservoirs, the exploitation priority can be ranked. The greater the values, the higher the priority of exploitation.

4 Applications

Ten exploited coalbed methane reservoirs in China are given here to verify the practicability of the comprehensive evaluation model, and related basic data are listed in Table 2 (Jiang et al, 2001; Krooss et al, 2002; Ma and Yin, 2002; Song, 2000; Ye, 2006; Wang and Wang, 2007).

A program based on the comprehensive evaluation model established in this paper was developed to determine the exploitation priority, and the computed results are shown in Table 3.

Table 2 Basic data of coalbed methane reservoirs

Reservoir name	Permeability $10^{-3}\mu\text{m}^2$	Gas content m^3/t	Depth m	Thickness m	Pressure MPa	Saturation %	Porosity %	Hydrogeologic appraisal	Adsorbability
Jincheng	0.98	16.1	700	7.5	3.77	91.8	6.64	Good	Good
Yangquan	0.25	17.2	600	9.1	4.12	92.5	5.04	Good	Good
Wubu	1.6	10.58	950	13.1	11.09	90.8	2.1	Medium	Good
Ningwu	0.86	14.8	850	19	8.7	86.29	1.9	Good	Medium
Dacheng	0.35	10.25	750	23.6	11.5	87.4	3.7	Good	Good
Hancheng	2.01	10.37	700	11.5	8.29	86.4	4.0	Bad	Medium
Huaibei	1.32	9.2	750	35	8.04	83.2	2.2	Medium	Bad
Fuxin	0.45	9.86	800	45	6.7	81.4	3.6	Bad	Medium
Tiefa	0.8	13.6	850	30	4	83.9	1.6	Medium	Medium
Kailuan	0.14	10.2	820	20	5.82	84.3	1.2	bad	medium

Table 3 Ranking results

Sequence	Reservoir name	Evaluation value
1	Jincheng	0.7851
2	Hancheng	0.7517
3	Ningwu	0.7167
4	Wubu	0.6979
5	Dacheng	0.6464
6	Yangquan	0.5812
7	Tiefa	0.5761
8	Huaibei	0.5715
9	Fuxin	0.5519
10	Kailuan	0.5316

The results show that the sequence of evaluation values is properly in agreement with the actual cases. As a matter of fact, the test results reflect the actual exploitation cases of the ten coalbed methane reservoirs. With perfect geological and reservoir conditions, Jincheng, Hancheng and Dacheng blocks were developed successfully. In the south of the Qinshui Basin, a national demonstration field has been built

up. On the contrary, the exploitation result of the Kailuan (low permeability, bad hydro-geologic appraisal) and Huaibei blocks (extensional structure results in the loss of coalbed methane) are not so satisfactory.

5 Conclusions

1) A comprehensive evaluation model combining neural network and genetic algorithm was successfully established to determine the weights of sensitive parameters, and this model can avoid the risk of trapping into local minimum points by the use of genetic algorithm.

2) Test results show that the comprehensive evaluation model is well able to decide the exploitation priority of coalbed methane reservoirs. This method can be used conveniently and easily in the decision making for exploiting coalbed methane reservoirs.

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