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Application of Neural Network to Reservoir Porosity Prediction

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Abstract. This paper discusses the methods for predicting reservoir porosity from relatively few data during the exploration period. The depth, thickness, lithology and ratio of sandstone to reservor are selected to build a neural network. After network training, a stable network structure is established. Using this neural network to calculate the porosity of reservoirs sets up the relationship between different influential factor sand porosity, and can also determine the degree to which porosity is affected. This method is used in Denglouku group of Songliao basin and the prediction results show a higher precision than normal mathematic fitting method and this method proves to be easier and more efficient.

Keywords: Petroleum and Gas Exploration, Neural Network, Reservoir, Porosity Prediction

1. The Introduction

Since 1988, some universities and companies in the United States have introduced the neural network to the oil industry and carry out a series of research on the application of the neural network in the petroleum exploration and development; Since 1990, many domestic scholars also have carried out the researches in this aspect[1~5]. The author studied the method of applying neural network to predict reservoir porosity, in order to determine the reservoir porosity without enough information.

2. The Basic Principle

The neural network is a system that simulates biological neural, which is formed of some parallel neurons in layer connected massively. A neural network has three basic elements: processing unit, neuron, network structure and learning algorithm. The neuron is the elementary element of the neural network, and it is usually a nonlinear unit with multiple input and single output. Network structure refers to the connection between neurons. The adopted BP network is a kind of feedforward neural network with layer structure, and it consists of an input layer, an output layer and one or several hidden layers between input layer and output layer. The common connection pattern is: each neuron only connects with the neuron in its adjacent layer, and the neurons in the same layer do not connect each other, and the information is only sent to output layer along input layer. The learning algorithm is a process that mainly makes the network in the output layer approach the expected output through inputing a set of information in the input layer of the network, and this process is called learning or network training of the network, and implementation steps and methods of this process are referred as the learning algorithm. In a variety of learning algorithms, the backward error propagation algorithm, namely the BP algorithm, is the most widely used, and the practice has proved that this method is effective in the interpretation of reservoir evaluation.

The key of the learning algorithm of BP neural network is: the network output error is attributed to the fault of connection weight, and by propagating backward the error of the output layer unit layer by layer to the input layer, namely sharing the error to each layer unit, the reference error of each unit is attained, so as to adjust the corresponding connection weight. Then adjust right repeatedly until the error between network

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output and expected output reduces to the allowed range. Once the network learning process is completed, connection weight will no longer change, then the system model described by the network will be fixed. For the new input data, the network will get the new output results after forward propagating, and that means network prediction can be realized.

Multiple factors influencing on reservoir physical property can be considered with the method of the neural network. By the learning process of known data, a convergent and stable network structure of the relationship between properties and various influencing factors is built eventually. The established network model can be applied to predict the reservoir properties of the unknown area.

3. Influencing Factors of Reservoir Porosity

Geological factors that influence the porosity are buried depth and structural location, sedimentary environment, lithology changes, diagenetic degree, etc.

Buried depth determines the burial and compaction process of reservoir, with the largest impact on the physical properties of reservoir. Porosity of clastic rock strata gradually decreases with the buried depth increasing generally, but in different plane position the degree of decrease is different.

The influence of lithology on reservoir physical properties is also very large. And from the argillaceous siltstone to glutenite, as the change of size of detrital grain and content of the shale, porosity value has its corresponding change rule.

The thickness of the reservoir also has effect on its physical properties. The physical properties of too thin sandstone formation become worse, because it is influenced by upper and lower argillaceous rock formation, while the physical properties of the thick sandstone layer are relatively well.

The influence of depositional environment on reservoir physical properties has been qualitative explanation[6]. Due to the different sedimentary sequences are formed in different sedimentary environment, the ratio of sandstone to reservoir is different. The relationship attained by statistics between different sedimentary facies and the value of ratio of sandstone to reservoir is shown in table 1. It can be seen that sedimentary facies can be reflected with the value of the ratio of sandstone to reservoir, then the influence of depositional environment on reservoir physical properties can be determined.

Table 1: The value of the ratio of sandstone to reservoir of various sedimentary environment in Denglouku Group in the north of Songliao Basin

Sedimentary facies	Statistical points	Maximum	Minimum	Average	Variance
Fluvial facies	25	0.661	0.050	0.336	0.141
Braided river plain facies	13	0.581	0.287	0.460	0.094
River alluvial plain facies	3	0.518	0.464	0.490	0.027
Floodplain	3	0.561	0.310	0.437	0.125
Fan delta	2	0.537	0.479	0.508	0.041

4. Application and Discussion

Deep reservoir in the north of Songliao Basin is new major exploration area in Daqing oil field. So far, industrial flows have been found in many prospecting wells. Deep oil and gas comes from the dark mudstone in the Shahezi-Yingcheng Group, and the Denglouku Group is the main reservoir of deep oil and gas. The BP neural network is applied to predict the porosity of the reservoir.

4.1. Establish the prediction neural network

(1) Preparation of learning data. Collect logging data of mainly prospecting wells in Xujiaweizi Region in the north of Songliao Basin. The buried depth, lithology, thickness and ratio of sandstone to reservoir are respectively read from logging data, and the porosity value is the effective value calculated based on logging data.

(2)The design of the neural network. Determine the number of the input neurons, neurons in hidden layer and output neurons, choose the excitation function and connection mode, set up the learning process parameters, namely learning rate, the momentum factor and learning times .etc. After the trial, Application of three layers BP neural network is determined. 4 neurons are chosen in input layer, which are respectively buried depth, lithology, thickness and ratio of sandstone to reservoir, 7 neurons in the middle layer and 1 neuron in output layer, that is porosity value. The neural network structure is shown in Fig. 1. The excitation function is

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

Learning rate and other parameters are adjusted dynamically in the process of learning, so as to ensure that the results of learning can attain the maximum fitting accuracy.

(3) The training process. The convergence of the network training process is determined through analyzing variance and correlation factor.

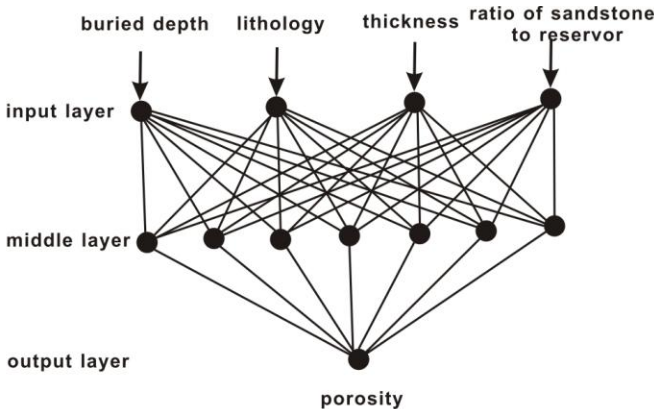

Fig. 1: The neural network structure that predicts porosity

4.2. Reliability analysis

The self-programming and general neural network QNET software is applied to standardize the learning data and control learning rate automatically, so as to avoid excessive training. A percentage of the learning data is chosen as test data, and the convergence of the network is tested at the same time of learning. The network learning results can be attained by the display of the parameters such as correlation degree, sum of squares of standard variance and the accuracy within the scope of permissible error, the related various maps can be attained at the same time.

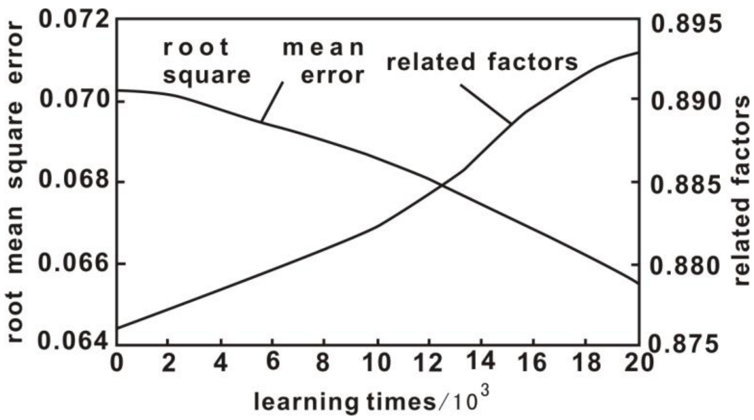

Fig. 2: The related factor curves of the root mean square error of predicted value and measured value of porosity in Well Chaoshen 4

After 20,000 times of learning, a stable and convergent of the network is attained finally. In the process of learning, change curve of overall root mean square error and the related factor of porosity of Well Chaoshen 4 is shown in Fig. 2. With the increase of the number of learning, root mean square error shows up a downward trend, but the related factor between the network output and the actual results showes up a trend of increase. Eventually root mean square error is 0.065, and the related factor is 0.893.But for the same data, if exponent fitting is only carried out with depth and porosity, the related factor is only 0.630. If the lithology, thickness and ratio of sandstone to reservoir are not considered, the neural network is only analyzed with depth and porosity value, the related factor is 0.800. Thus, reservoir physical properties analyzed with the neural network method synthesized with many factors can attain relatively high precision.

The impact degree of these factors that influence the reservoir property on the porosity value is found different through calculating, the respective contribution as shown in Fig 3. The Fig. 3 shows the largest contribution is made by depth, the second is the thickness and the ratio of sandstone to reservoir on behalf of the sedimentary environment, and lithology makes the relatively small contribution. But this relationship is not the only one, because the concrete condition of each well is different, the influence degree of various factors on the porosity of Well Zhaoshen 5 as shown in Fig. 4.

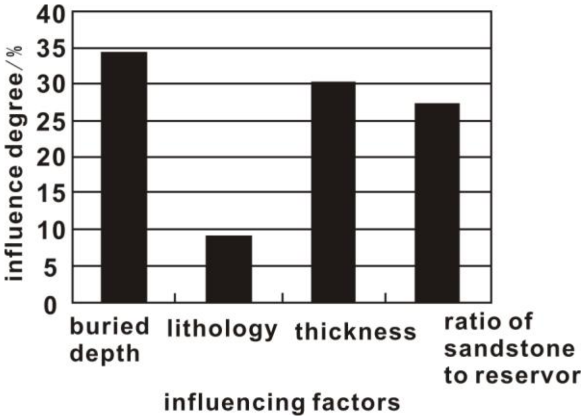

Fig. 3: The influence degree of various factors on the porosity of Well Chaoshen 4

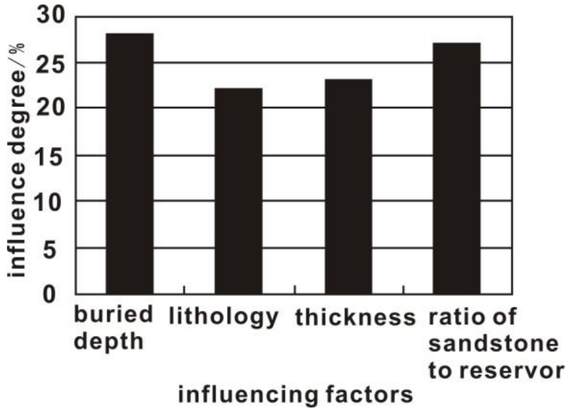

Fig. 4: The influence degree of various factors on the porosity of Well Zhaoshen 5

4.3. Predicting outcomes

After training, the established neural network makes sure the connection weights of each layer of network, and forms a stable network structure. The network is applied to predict the porosity of deep Denglouku Group in the north of Songliao Basin, the prediction results as shown in Fig. 5. The Fig. 5 shows that in the center of the sag, the porosity is low, while the porosity is relatively high at the edge of the sag area, and that is consistent with the actual situation.

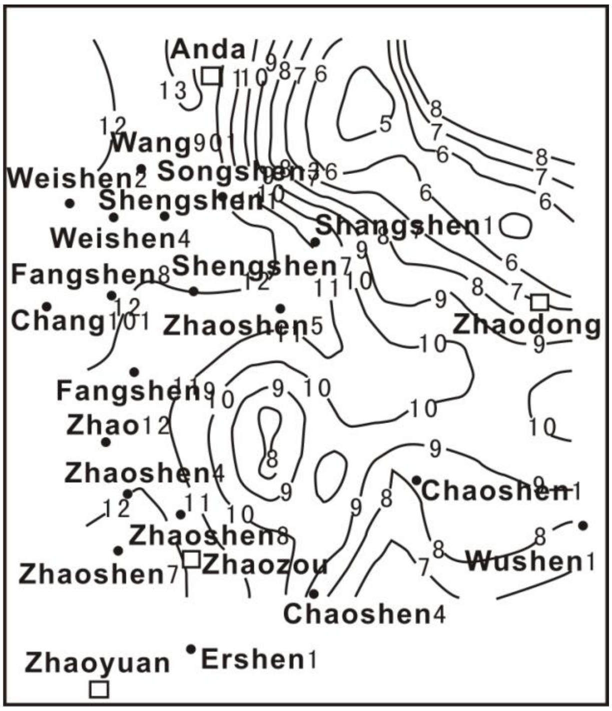

Fig. 5: The predicting outcomes of the porosity of Denglouku Group in the north of Songliao Basin

5. The Conclusion

It does not need a large amount of data for using neural network technology to predict the porosity, and also do not need to get the relationship between the parameters, that is, according to the known data we can predict the physical properties of new areas maximumly, at the same time get the degree of the influence on porosity from each factors in different regions. It is fast and effective for applying this method to predict porosity under the condition of the early exploration stage without sufficient information.

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