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Productivity Prediction of Tight Sandstone Reservoir Based on BP Neural Network

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Abstract

To survey He-8 member tight sand reservoir with low porosity and permeability in Mizhi gas field in Ordos basin, using the conventional well log data, this paper proposes the tight sand reservoir productivity prediction model and classification criterion based on BP neural network, getting quick classification of gas well productivity. We can predict sand reserve quantitatively instead qualitatively with the methods. Applications show that the methods of productivity prediction are effective and practical.

Key words: Productivity prediction; Low porosity; Low permeability; Tight sandstone; Neural network

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INTRODUCTION

Tight sand reservoirs with low porosity and permeability are widely distributed in Ordos basin, and Mizhi gas field is the typical representative of low-permeability tight sandstone gas reservoirs. Reservoir productivity prediction is a quite important aspect of oil and gas exploration. It is a comprehensive evaluation index of formation quality, fluid property and oil production capacity, and it's also one of the most important indices in the meantime. Many geologists, reservoir engineers and logging analysis experts did a lot of work in it[1-3]. The reservoir physical parameters calculated by logging data mainly reflect the static characteristics of the reservoir, and they cannot directly reflect reservoir's dynamic characteristics. The main purpose of reservoir productivity prediction using logging data is to try to predict the dynamic changes by static data. Selecting He-8 member in Mizhi gas field in Ordos basin as study object, this paper proposes the tight sand reservoir productivity prediction model and classification criterion based on BP neural network, which can get quick classification of gas well productivity[4-7]. And it has achieved a rather satisfactory result in practice.

1. THE PRINCIPLE OF NEURAL NETWORK

Neural network is currently one of the most widely used methods of reservoir identification and evaluation, which has good characteristics of self-adaptive and self-learning. It is composed of the dissemination of positive information and error back-propagation[8-10]. In the process of positive information dissemination, we can obtain the output value of every neural units according to the theory of neural network once logging value is input; in the process of error back-propagation, predicted productivity by neural network should be compared with the oil testing conclusion and do the recursive computing layer by layer until the errors between them meet the prediction accuracy requirements of daily oil production. During the course of modeling, the oil testing data and corresponding routine well logs of the key wells in the study area should be preprocessed firstly so that they can meet the needs to network training. Then, all the valid data were divided into two parts: training samples and diagnostic samples. The system is trained according to the training sample data set to adjust the network weight matrix, and then utilize the data of diagnostic samples to test the prediction effect of oil production per meter.

1.1 The Step of Realizing Artificial Neural Network

The flowchart of realizing artificial neural network is shown in Figure 1, and the specific steps are as follows:

(a) Initialize the weight of each layer randomly:

The weight from input layer to hidden layer is W_{ij}=Random( ).

The weight from hidden layer to output layer is W_{jk}=Random( ).

(b) Input m learning samples of logging data, including porosity, shallow resistivity, deep resistivity and relative GR, and record the current number of input samples as n.

(c) Calculate the output results of each layer's neuron, recording the output value of hidden layer as x_j and the output value of output layer as y_k.

(d) Calculate the back propagation error by the formula as following, where p is the number of training samples:

$$\delta_{jk}^{(p)} = (d_1^{(p)} y_k^{(p)}) y_k^{(p)} (1 - y_k^{(p)}) .$$

(e) If $p<m$, turn step (2) to continue to calculate. And if $p=m$, turn step (6) to continue to calculate.

(f) Correct the weight of each layer according to the theoretical formula of neural network.

(g) Recalculate x_j, y_k and the total error E according to new weights until $E<\gamma$ (A given value, e.g 0.001) or the computing times live up to the maximum training times. Or turns step (2) to continue to a new round training.

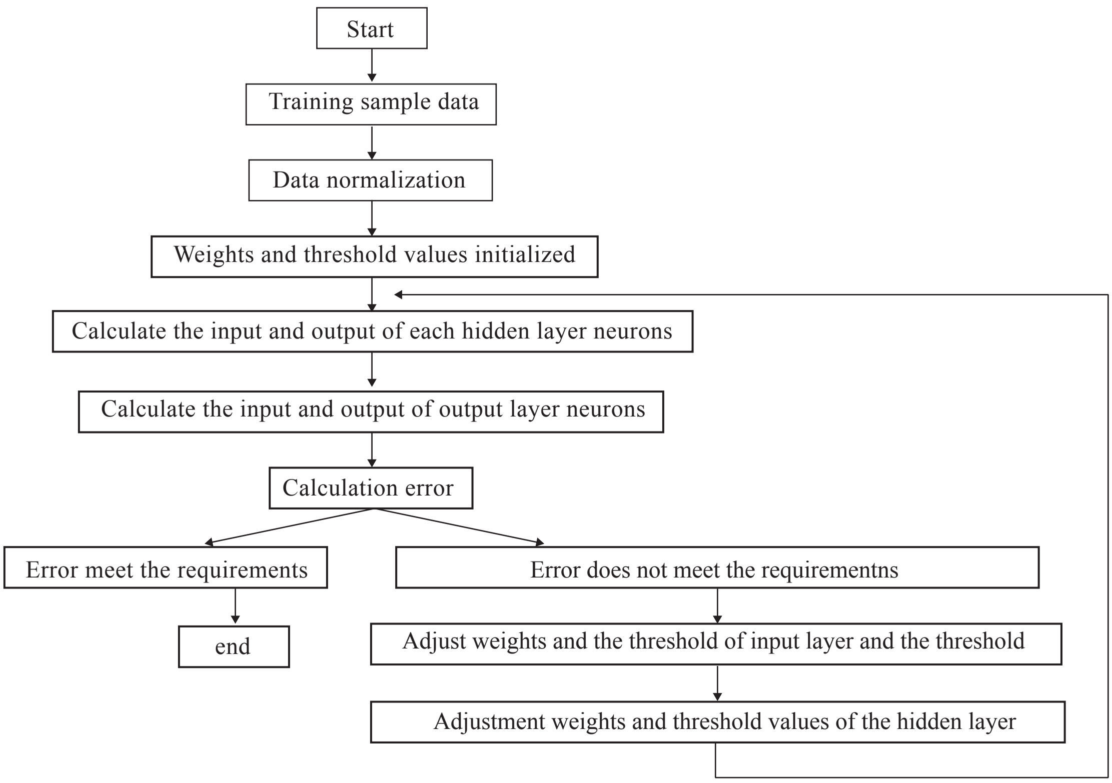

Figure 1
The Flow Chart of the Method of Productivity Prediction Based on BP Neural Network

1.2 The Determination of Input Parameters of Neural Network

The natural productivity of oil and gas reservoirs is affected by many factors, including the two major categories. One is the controlling factors of reservoir, such as lithology, physical properties, oil-gas potential, fluid properties, effective thickness of the reservoir and so on. The second is engineering factors, including the skin factor, testing radius, etc.. Without consideration of the influence of engineering factors, the natural productivity is mainly affected by reservoir characteristics. It can eliminate the influence of thickness of layer that using oil production per meter to evaluate the productivity, which is defined as daily oil production divided by thickness of layer. Due to the high heterogeneity of tight sandstone reservoir and the intense variations of pore structure and physical properties, it's hard to compute permeability and saturation. However, Figure 2 cross-plot presents significant positive correlation between deep resistivity and oil production per meter, and that means the value of deep resistivity can indirectly evaluate oiliness of reservoir.

After reservoir classification, the sample number in each type of reservoir significantly less than it when not classified. And in order to avoid appearing underdetermined system of equation when solving weights and threshold values caused by profuse nodes in the input layer and hidden layer, well logs can be classified by lithology, physical properties, oil-gas potential firstly when choosing input parameters. Next, selecting input parameters from each catagory to reduce the number of input parameters. Then, analyzing the relationship between the oil production per meter with conventional logging and array induction logging by simple correlation, and selecting logging parameters having better correlations with oil production per meter respectively from three categories. After analyzing, the relative value of GR, porosity, deep resistivity and shallow resistivity of the array induction logging are imported into the trained neural network model (Figure 2).

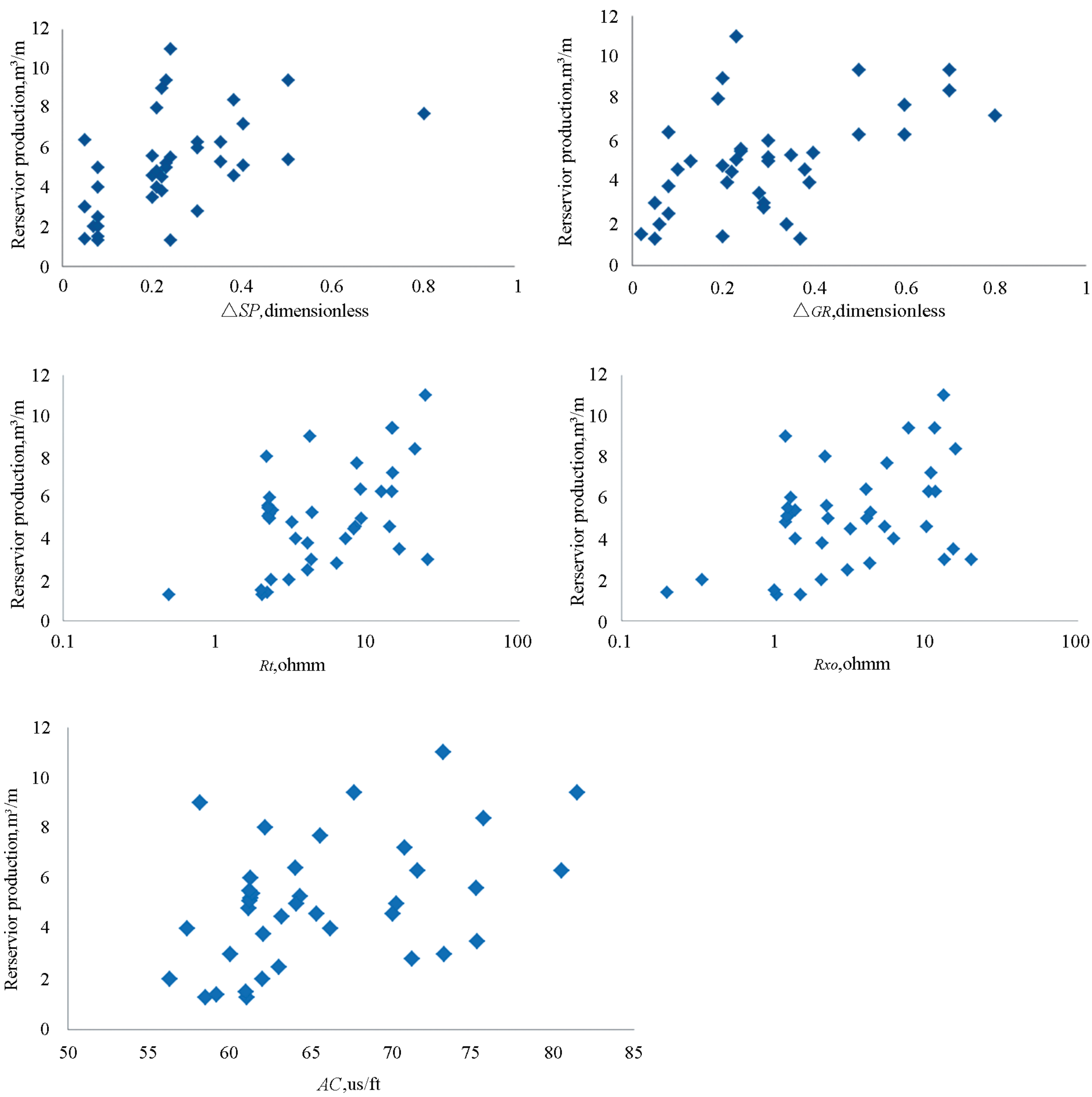

Figure 2
Logging Information and Reservoir Production Crossplot

1.3 The Determination of the Structure of Neural Network

The number of hidden nodes in the neural network model has significant effect on the neural network performance[11-14]. Too few numbers of hidden nodes will cause the output of neural network model failed to approach the expected value; nevertheless, too many hidden nodes will lead to an excessively long training time and easily get trapped in a local optimum. Comparing the results of the prediction effect under different number of hidden layer nodes, 5 hidden nodes were selected. And Figures 3 is the structure chart of the neural network.

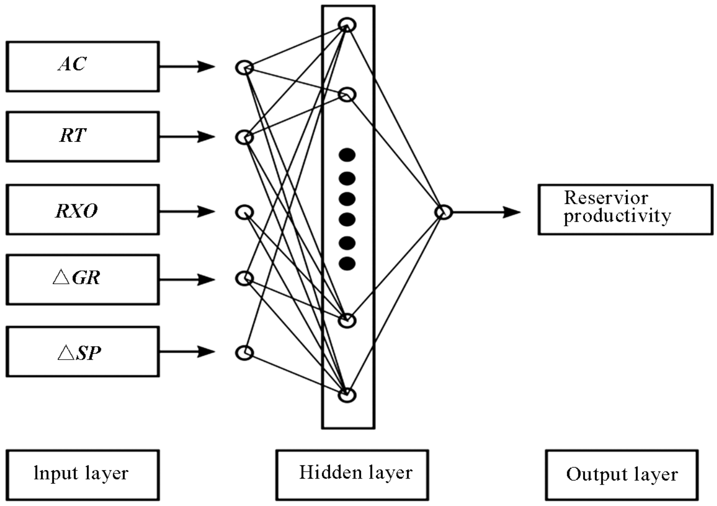

Figure 3
The Structure of the BP Neural Network

1.4 The Selection and Pretreatment of Training Samples for Neural Network

Firstly, choose the samples with validity, representation, continuity and comprehensiveness as training samples for neural network; in the meantime, delete the obviously abnormal outliers during the simple correlation analysis for fear of influencing the stability of the network[15-16]; then, normalize each input parameter of selected samples to ensure a similar convergence rate. In the paper, the reservoir is classified into three categories according to the displacement pressure, and three kinds of reservoir productivity prediction models are established respectively.

1.5 The Validity Check of Neural Network Training

Three kinds of prediction models are applied to the wells not used to establish models, and Table 1 shows the comparison results between the computational conclusions and oil testing conclusions of layer samples. It can be seen that there are 6 layers classified as type-Ⅲ reservoirs, 8 layers classified as type-Ⅱ reservoirs and 10 layers classified as type-Ⅰ reservoirs. 20 layers were correctly predicted; 4 layers got the wrong results. The coincidence rate of prediction results was up to 83.3%. If the models were established without considering the differences of reservoirs, the coincidence rate of prediction results was only 62.5%.

Table 1
Test Table of the Prediction Results Through Neural Network Based on Three Types of Reservoir Classification

Well	Depth/m	Layer thickness /m	Prediction results of unclassified reservoir/m^3	Prediction results of classified reservoir/m^3	Actual results /m^3
M7-06	X530.1-X539.8	9.7	6.5	9.5	10.2
M7-06	X561-X564	3	0.5	1.8	1.5
M7-06	X566-X572.4	6.4	2.3	2.9	3.4
M7-06	X583-X585	2	1.2	3.8	4.3
M22-21	X341.2-X346.5	5.3	3.2	7.3	6.4
M22-21	X351-X356	5	1.3	2.1	1.8
M22-21	X367.3-X376.1	8.8	3.4	5.2	5.6
M25	X211-X216.5	5.5	1.5	6.2	6.5
M25	X222.2-X226.3	4.1	0.4	4.1	3.6
M25	X231-X233.4	2.4	0.8	2.1	1.3
M25	X241.5-X246	5.5	1.8	7.2	6.8
M25	X252.6-X260.3	7.7	3.1	9.8	12.3
S136	X625-X632.3	7.3	2.3	8.7	9.4
S136	X635-X640.1	5.1	4.8	5.6	6.2
S136	X641-X646.2	5.2	0.9	7.2	6.5
S136	X651-X659.1	8.1	3.1	8.9	9.8
S136	X670-X674.8	4.8	1.6	5.4	5.3
S136	X679-X683.4	4.4	0.3	4.1	3.9

2. THE APPLICATION OF PRODUCTIVITY PREDICTION METHOD

Figure 4 is the plot of processing the results of a new exploration well, and the oil testing result of 16^{th} layer shows the natural production for oil. It can be seen from the 7^{th} track of the plot that the layer have porosity of 15%, so its pore structure should be classified as the type-Ⅰ reservoir and adopts the type-Ⅰ neural network model. The prediction result of oil production per meter shows in the 8th track, 5.8 $m^3/(d \cdot m)$. The value multiplies by the thickness of layer 8.5 m makes the prediction result of 16th layer oil production 12.2 m^3/d. The oil test results proved the rationality of the method, and the prediction accuracy meets the production requirements.

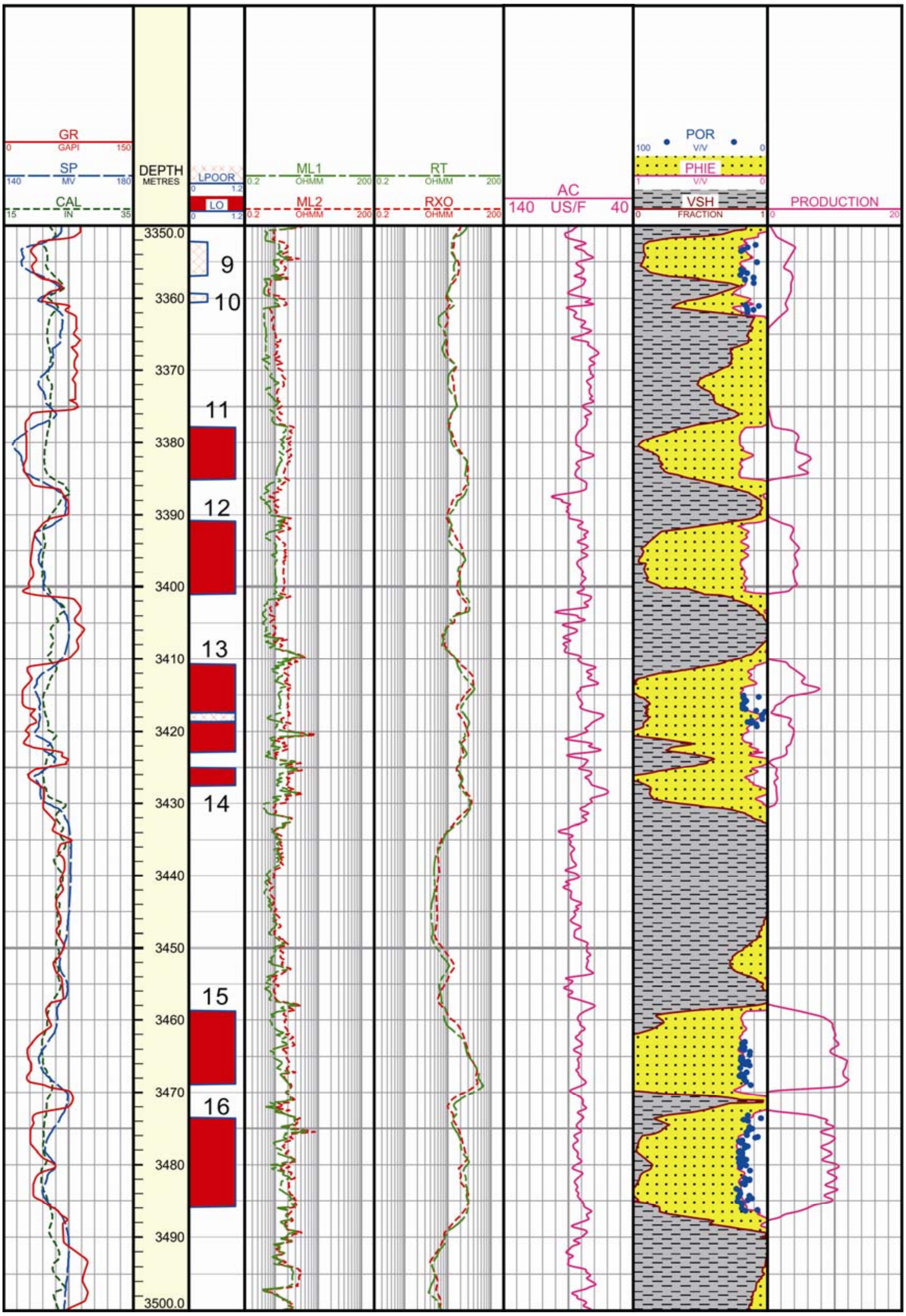

Figure 4
The Well-B Productivity Prediction Result of He-8 Member in Mizhi Gas Field in Ordos Basin

CONCLUSION

(a) The complicated deposit process of Mizhi gas field leads to the complex pore structure, so it's hard to predict productivity.

(b) The effect of productivity prediction based on well logging mainly depends on the calculation precision of reservoir basic physical parameters and the evaluation accuracy of fluid property.

(c) According to the characteristics of the formation, combined with conventional logging and mercury injection data, the natural productivity production model suitable for the study area is built based on neural network by optimizing logging parameters and deeply analyzing the relationships between reservoir liquid yield with formation pressure and pore characteristics. And the good application results tested by production are achieved.

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