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Identification of Sedimentary Facies by Nerve Network in Shanxi Formation of Ordos Basin

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Abstract

To improve the accuracy of division of each sedimentary facies in Shanxi Formation of Lushi sag in Ordos basin, the single well factes of cored wells are researched, and the optimum quantitative parameters, which can reflect the characteristics of various sedimentary factes, are calibrated quantitatively. Inputting the result into the nerve network system, the automatic identification of unknown sedimentary facies is done by the automatic identification and adjustment of weighted value of nerve network's intelligent function. The nerve network technique is used to divide sedimentary facies in Shanxi Formation, and the result is expected. The technique is playing an important role in improving efficiency and accuracy of analysis and interpretation of the sedimentary facies.

Keywords: *Nerve network, Sedimentary factes, Shanxi Formation, Ordos basin.*

1. Introduction

Sedimentary facie analysis plays an important role in guiding the choice of the development wells, the layout of injection and production wells, and the measures of enhanced EOR reservoirs and so on[1]. For a long time, the research of sedimentary facies is mainly depending on the drilling coring data, which not only the high cost and low efficiency. It is very difficult to accurately divide sedimentary facies of without coring wells and unknown areas. To solve this problem, we use neural network model to identify sedimentary facies of without coring wells and unknown areas and get good results.

Neural network is a mathematical model similar to the human brain connection structure for distributed parallel information processing algorithms [2]. Based on its own unique sample learning ability to obtain recognition, BP neural network method, which has the self-organizing and self-learning, adaptive and anti-jamming capability, overcomes the shortcomings of fuzzy mathematics method [3], gray clustering method and multivariate statistical methods [4]. According to the BP neural network recognition sedimentary facies of logging parameters, the results are objective and reliable with high feasibility and credibility.

In this paper, identification and division of sedimentary facies in Shanxi Formation of Lushi sag of Ordos basin in China, for example, illustrate the implementation process and the application effect of neural network recognition sedimentary facies.

Shanxi Formation is the main oil and gas development purpose layer in Lushi sag of Ordos basin. Due to the sedimentary facies recognition is not clear, the development effect is not ideal [5]. Using the neural network model to identify the sedimentary facies reveals the distribution of sedimentary facies in Shanxi Formation, which provides the theoretical foundation for further oilfield development.

2. Methods and Principles

Based on the structure and function of the human brain, artificial neural network is an information processing system of simplify and simulation. Characteristics of neural network technology are a distributed storage of information, a large-scale adaptive parallel processing, and tolerance of error, etc., allow for a larger defect samples, and can handle the problem of very complex information, unclear background knowledge and unclear reasoning rules, this feature now applies to sedimentary facies explained in logging. Therefore, it is suitable for the interpretation of the sedimentary facies in logs.

At present, the artificial neural network model are mainly feedback neural network feed forward neural network, stochastic neural network, the self-organizing neural network, and so on [6]. Sedimentary facies analysis for network structure has a strong nonlinear mapping ability and flexibility [7]. In view of the practical problems, based on the analysis of several kinds of characteristics of network model, the feed forward network of the error back propagation algorithm (BP algorithm) is applicable in the interpretation of the sedimentary facies in the log.

Artificial neural network is similar to human intelligence, the network gets knowledge through learning, and then completes the pattern recognition and classification in the process of recognition of sedimentary facies. Therefore, the neural network pattern recognition process is divided into two steps to realize the network training and the pattern recognition.

2.1 Selecting reservoir evaluation parameters

The sample of a known type is as an input, and the known type is as a desired output. The sample from the input layer after computing gives an actual output on the output layer. Between the desired output and actual output will produce an error vector. Error back propagation method is used to modify the network connection weight between the layers, so that the output error decreases gradually, until the error between the desired output and the actual output achieves an acceptable level. As a result, the network training is successful and network knowledge is stored in the network connection weight.

Assume the input pattern vector is P, the input layer neuron number is r, the hidden layer neuron number is S_1, the output layer neuron number is S_2, the output vector is M, and the target loss into vector is T. Then the i-th neuron of a hidden layer is as follows:

$$A_{i1} = f\left(\sum_{j=1}^{r} W_{ij1} \cdot P_j + \theta_j\right) \quad i = 1,\ 2,\ \cdots,\ S_i \qquad (1)$$

In a similar way, the k-th neuron output is as follows:

$$A_{k2} = f\left(\sum_{j=1}^{S_1} W_{ik1} \cdot a_{i1} + \theta_k\right) \quad k = 1,\ 2,\ \cdots,\ S_2 \qquad (2)$$

Where W_{ij} is the connection weights between i and j; θ_j is the threshold of the node j; F is a nonlinear activation function using the Sigmoid function, that is, $f(x) = 1/(1-e^{-x})$

The update amount ΔWij of the connection weight Wij is as follows:

$$\Delta W_{ij} = -\varepsilon \frac{\partial r}{\partial P^k{}_j} M^{k-1}{}_j \qquad (3)$$

$$d^k{}_j = \frac{\partial r}{\partial P^k{}_j} \qquad (4)$$

$$\Delta W_{ij} = -\varepsilon \cdot d^k{}_j \cdot M^{k-1}{}_j \qquad (5)$$

Where ε is the learning step, a positive value.

The d^k_j of calculation formula is discussed as follows:

$$d^k{}_j = \frac{\partial r}{\partial P^k{}_j} = \frac{\partial r}{\partial M^k{}_j} \cdot \frac{\partial M^k{}_j}{\partial P^k{}_j} \qquad (6)$$

If j is the output layer (h-th layer) of the neurons, $K = h$, the y_j is the expected output of the network, as the constant value. Its formula is as follows:

$$d^h{}_j = M^h{}_j \cdot (1 - M^h{}_j) \cdot (M^h{}_j - y_j) \qquad (7)$$

If j is not in the output layer, it is in the middle of the hidden layer K, there are:

$$d^k{}_j = M^k{}_j \cdot (1 - M^h{}_j) \cdot \sum_{\mathrm{i}} W_{jl} \cdot d^{k+1}{}_l \qquad (8)$$

As you can see, the error signal d^k_j of K layer is proportional to the error signal $d^{k+1}{}_j$ on a layer.

Error function is the use of square type, and its formula is as follows:

$$E(W,B) = \sum_{k=1}^{S_2} (t_k A_{k2})^2 / 2 \qquad (9)$$

If the E value is less than the allowable error, the learning process is over. Otherwise, the output error is calculated for each node, which is the error back-propagation; the threshold value of the network connection weights is modified until the network converges, so that E is less than the allowable error.

2.2 Pattern recognition

The advantages of neural network are a self-organizing and self-learning ability. It does not need to establish identification rules, but uses specific learning algorithm to get recognition from the given instance of knowledge. Neural network learning rules are an algorithm of fixed structural connecting weight. In this paper, using the neural network learning algorithm is the most effective BP learning algorithm (error back propagation algorithm). The learning mechanism is for a given input mode. When the actual output and the desired output occur error, the network will automatically adjust the corresponding connection weight and reduces the error in the direction of change connection weight. After repeated study until convergence, the result is finally consistent with actual result, and the connection weight is as the knowledge preservation. So as to obtain the pattern recognition of sedimentary facies of intelligent knowledge, we can use this knowledge to the unknown well block identification of sedimentary facies.

3. Selection parameters

In order to effectively divide the sedimentary facies, all kinds of logging parameters should be used as much as possible.. But it is often the correlations between logging parameters, the sedimentary facies of information are often certain repeat, and brings great difficulty to neural network discriminant analysis. The characteristics of the sedimentary facies of the logging are analyzed by the coring section calibration logging curve. By using the principal component analysis, a few logging parameters, which reflect the characteristics of the sedimentary facies uncorrelated with the principal component, are extracted, so that they can be effectively integrated sedimentary facies information, as reflected in the original logging parameters. Thus only by a few principal components as discriminant analysis, neural network can achieve the goal of effective division standard sample layers of sedimentary facies.

According to the actual logging curve type and principal component analysis in the study area, the extraction in the distinguish of sedimentary facies is well logging curve value as neural network input item numerical variables. Log values to distinguish good from sedimentary facies are as neural network input item numerical variables, including natural gamma ray, spontaneous potential, acoustic, density, compensated neutron, and borehole diameter. The six parameters unrelated principal component are contributed more to the 95% of the original information. They reflect the logging parameters of the effective comprehensive sedimentary facies information, reduce the dimensions of the sample layer, and simplify the neural network discriminant analysis.

4. Identification sedimentary facies

Neural network program is compiled using the object-oriented language, the interactive automatic identification system of the logging of the sedimentary facies is developed, and the consecutive interpretation of sedimentary facies can be automatically completed in well profile.

According to the detailed study of coring well of sedimentary facies in Shanxi Formation of Lushi sag in Ordos basin, the characteristic parameters of the logging are selected as learning samples of neural network, and table 1 lists the part parameter of the learning samples. Based on 3000 learning samples after 185 times of network training and repeated testing and comparing the network layers and the number of hidden nodes, BP neural network structure model including the input layer nodes, the output layer nodes and the hidden layer nodes is identified (Figure 1), and the discrimination models of 16 types of sedimentary facies are established in the study area. The training error percentage, average incorrect percentage and incorrect standard deviation percentage are respectively 0.261%, 1.114% and 4.492%. Table 2 is the neural network analysis results of sedimentary facies with the core analysis results, two results are basically consistent. The logging characteristic parameters identification of sedimentary facies has a high accuracy.

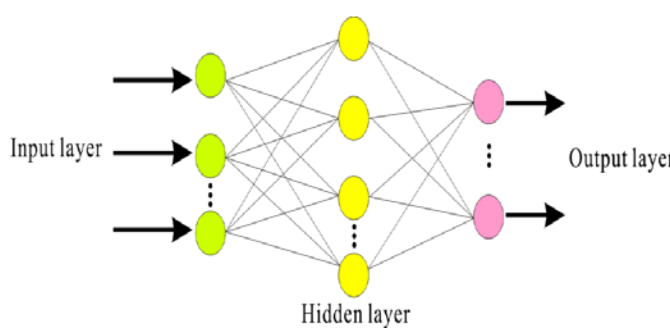

Fig. 1 BP network structure model with one hidden layer.

Table 1: Learning samples of neural network

D_{CALI} / cm^{-3}	Δt_{DT} /($\mu s \cdot m^{-1}$)	Φ_{CNL} /%	ρ_{DEN} /($g \cdot cm^{-3}$)	γ_{GR} / API	V_{SP} / mv	SF
15.79	99. 45	0.42	2.02	94.41	-18.65	A
13.89	83.98	0.28	2.56	117.41	-22.81	B
14.21	84.33	0.28	2.45	112.92	-22.31	B
13.67	79.54	0.31	2.31	85.63	-23.63	C

15.69	95. 879	0.33	2.25	88.40	-19.52	C
13.43	77. 567	0.21	2.46	76.32	-16.21	D
14.46	86.11	0.24	2.26	82.19	-18.14	D
13.33	75.11	0.18	2.50	72.72	-18.70	E
13.93	79.77	0.24	2.51	82.73	-21.64	E
11.53	83.13	0.28	2.41	94.87	47.87	F
12.05	84.15	0.29	2.53	84.80	56.10	F
12.04	84.04	0.27	2.54	80.23	53.21	G

Note: SF is sedimentary facie, A is braided delta plain, B is braided delta front, C is delta plain, D is delta front, E is alluvial plains, F is shallow-shore lake, G is semi-deep lake.

Table 2: Comparison sedimentary facies of ANN and well core interpretation

No. well	*Strata depth/ m*	*NNISF*	*GASF*
GX1	－3231.5～－3239.3	E	E
GK7	－3243.4～－3253.6	A	A
GH4	－3353.6～－3356.2	B	B
GF2	－3356.8～－3363.5	C	C
GT8	－3363.1～－3374.4	D	D
GD3	－3364.4～－3375.6	D	D
GS4	－3375.6～－3382.5	F	F
GA5	－3385.9～－3392.3	G	G

Note: NNISF is neural network interpretation of sedimentary facies, GASF is geology analysis of sedimentary facies, A, B, C, D, E, F and G are the same as Table 1.

In order to test the validity of the result of the automatic identification of sedimentary facies, 276 samples from 3 wells show that with the actual coincidence rate reaches 95% (Table 3), so that the automatic recognition results are high accuracy.

Through the method of identification of sedimentary facies, the ultimate goal is to divide the distribution map of sedimentary facies, to delineate favorable reservoir distribution area and to provide scientific basis for the development of oil and gas fields. Fig. 2, Fig. 3 and Fig. 4 are the distribution map of sedimentary facies of Q1, Q2 and Q3 sequence from bottom to top in Shanxi Formation of Lushi sag in Ordos basin. The figures show the sedimentary period of the basin from expansion to contraction and the water from deep to shallow in Shanxi Formation. The distribution of the sedimentary facies in SQ1, SQ2 and SQ3 sequence is different in north and south of the basin. In the north of the basin with strong tectonic activities and the terrain elevation, the sedimentary facies of the braided delta is developed. In the south of the basin with tectonic stability and gentle terrain, the sedimentary facies of the delta is developed. The sedimentary sandbody of delta front and braided delta front is the most favorable reservoir in this area.

From the above shows that neural network recognition of sedimentary facies can well solve the division of sedimentary facies in an area of less coring wells.

Table 3: Neural network identification results of sedimentary facies

No. well	*GH9*	*GD5*	*GP2*	*Total*
SQ	94	75	54	223
C	83	68	47	198
%	88.3%	9.7%	87.0%	88.8%
PC	6	4	5	15
%	6.4%	5.3%	9.3%	6.7%
E	5	3	2	1
%	5.3%	4.0%	3.7%	4.5%
CR	94.7%	96.0%	96.3%	95.5%

Note: SQ is sample quantity, C is correct, PC is partial correct, E is error, CR is coincidence rate.

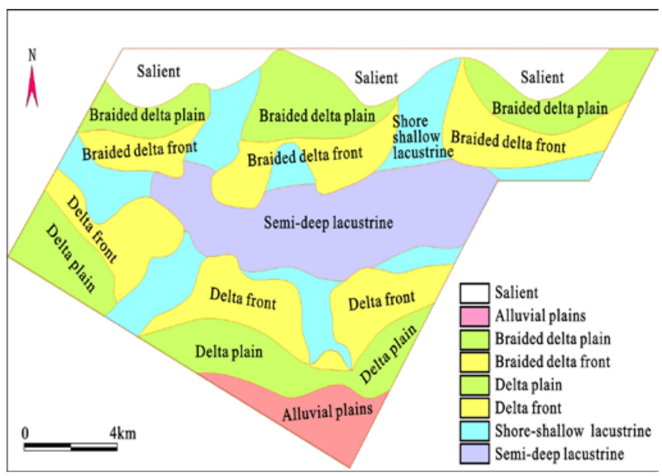

Fig. 2. Distribution of sedimentary of SQ1 sequence facies in Shanxi Formation

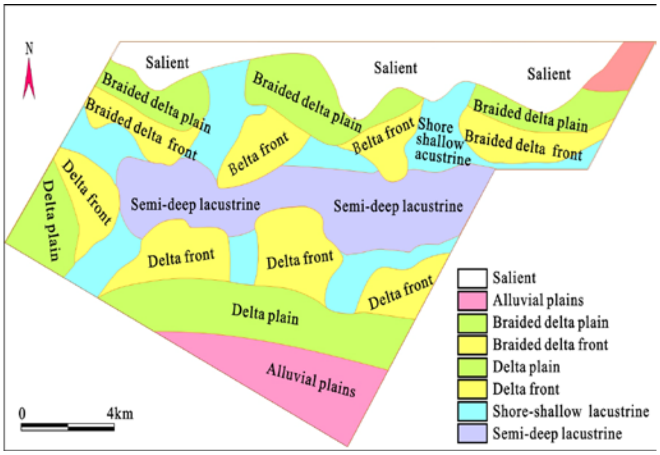

Fig. 3. Distribution of sedimentary facies of SQ2 sequence in Shanxi Formation

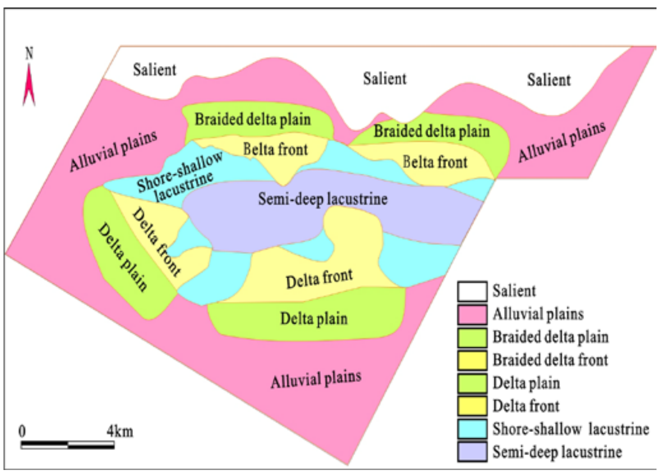

Fig. 4. Distribution of sedimentary facies of SQ3 sequence in Shanxi Formation

5. Conclusions

Under the condition of less drilling coring in the oil and gas exploration and development, neural network pattern recognition of sedimentary facies is to solve the identification and division of sedimentary facies in the non-coring area, and it can make the interpretation automation of the sedimentary facies.

In the study area， the log data for analysis of sedimentary facies are the natural gamma ray, spontaneous potential, acoustic, density, compensated neutron, and borehole diameter. The different sedimentary facies have the response of the different log, which is the basis of the use of neural network identification of sedimentary facies.

Neural network identification of sedimentary facies and core division results have very good coincidence rate. The method to identify sedimentary facies has high recognition speed and stability, but also has good prospects.

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First Author Profile

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