Evaluation Method of Reservoir Heterogeneity Based on Neural Network Technology

Shasha Yang\textsuperscript{1*}, Ying Chen\textsuperscript{2}, Yong Yang\textsuperscript{3}, Kekuo Yuan\textsuperscript{1} and Juanjuan Quan\textsuperscript{1}

\textsuperscript{1}School of Civil Engineering, XiJing University, Xi’an, Shaanxi, 610500, China
\textsuperscript{2}Zhidan Oil Production Plant, Shaanxi Yanchang Petroleum (Group) Co. Ltd., Yan’an, Shaanxi, 716000, China
\textsuperscript{3}Fuxian Oil Production Plant, Shaanxi Yanchang Petroleum (Group) Co. Ltd., Yan’an, Shaanxi, 727500, China

*Corresponding author e-mail: 20190100@xijing.edu.cn

Abstract. Reservoir is the underground storage and accumulation place of oil and natural gas. The accuracy of reservoir heterogeneity evaluation has great economic value for correctly guiding the production and development of oil and natural gas. The high-order neural network method is used to comprehensively evaluate the heterogeneity of the reservoir. This method was applied to the evaluation of reservoir heterogeneity in the PK area. The results show that the heterogeneity of sandy clastic flow sand bodies is the weakest, the sandy landslide sand bodies are medium, and the turbidity current sand bodies are strongest. The evaluation method of reservoir heterogeneity based on high-order neural network technology effectively solves the problem of inconsistent conclusions of single-parameter evaluation of heterogeneity in conventional methods, and can quantitatively characterize the degree of reservoir heterogeneity.

Keywords: Neural Network, High-Order Neural Network, Reservoir Heterogeneity

1. Introduction
Reservoir is the underground storage and accumulation place of oil and natural gas, and it is the direct target of oil and gas exploration and development. Reservoir heterogeneity refers to the spatial heterogeneity of the parameters that characterize the reservoir. It is a universal characteristic of the reservoir. The accuracy of its evaluation has great economic value for correctly guiding the production and development of oil and natural gas [1, 2]. The research methods of reservoir heterogeneity are diverse, and commonly used evaluation indicators include: permeability variation coefficient $V_i$, permeability penetration coefficient $T_i$, permeability difference $J_i$, distribution frequency of muddy interbeds $P_i$, and distribution density of muddy interbeds $D_i$, etc. [3].

When evaluating reservoir heterogeneity in actual production, it is often affected by various factors such as the complexity of the underground geology, the accuracy of data measurement, and the completeness of the theory, resulting in the conflicting evaluation results of the aforementioned
indicators [4, 5]. In response to this, the predecessors proposed to obtain a comprehensive index based on mathematical methods to evaluate reservoir heterogeneity. For example, the entropy weight method of Yang Shaochun et al [6], and the Lorentz curve method of Liu Chao et al [7], have achieved good results in specific research areas. However, the entropy weight method relies on sufficient sample data and actual problem domains. The calculation is complicated, and the participation is poor. It cannot reflect the importance of the judges on different attribute indicators. Sometimes the weight will be quite different from the actual importance of the attribute. The Lorentz curve method only uses permeability data to define a new characterization parameter of reservoir heterogeneity, which cannot fully reflect the characteristics of reservoir heterogeneity.

In order to solve the above problems, this paper proposes a comprehensive evaluation method of reservoir heterogeneity based on high-order neural network, which can not only solve the problem of inconsistent results of single parameter evaluation heterogeneity, but also reflect the reservoir heterogeneity comprehensively and quantitatively. This method can be continuously iteratively optimized based on new production data, which is expected to further improve the accuracy and timeliness of the understanding of reservoir heterogeneity in the oilfield production process.

2. Commonly Used Reservoir Evaluation Indicators

Evaluation indicators of reservoir heterogeneity widely used by scholars at home and abroad include: permeability variation coefficient $V_i$, permeability penetration coefficient $T_i$, permeability difference $J_i$, distribution frequency of muddy interbeds $P_i$ and distribution density of muddy interbeds $D_i$, etc.

Permeability variation coefficient

$$V_i = \sqrt{\frac{\sum (K_i - \bar{K})^2 / (n-1)}{\bar{K}}}$$ (1)

Permeability penetration coefficient

$$T_i = \frac{K_{\text{max}}}{\bar{K}}$$ (2)

Permeability difference

$$J_i = \frac{K_{\text{max}}}{K_{\text{min}}}$$ (3)

Distribution frequency of muddy interbeds

$$P_i = \frac{N}{H}$$ (4)

Distribution density of muddy interbeds

$$D_i = \frac{h}{H} \times 100\%$$ (5)

Where: $K_i$ is the permeability value of a single sample, $n$ is the number of samples, $\bar{K}$ is the average permeability of all samples, $K_{\text{max}}$ is the maximum permeability of all samples, and $K_{\text{min}}$ is the minimum permeability of all samples. $\bar{K}$, $K_{\text{max}}$ and $K_{\text{min}}$ can be obtained through logging data or physical property testing. $N$ is the number of interlayers (non-permeable or relatively low-permeable layers located inside the sand layer, usually mudstone, silty mudstone, argillaceous siltstone or calcareous sandstone), $h$ is the total thickness of the interlayer, in meters, $H$ is the studied reservoir total thickness, in meters. $N$, $h$ and $H$ can be obtained through logging data or core observation statistics.
3. Evaluation Method of Reservoir Heterogeneity Based on High-Order Neural Network

The high-order neural network is an extension of the multilayer perceptron neural network. It is based on the basic model of the perceptron, adding auxiliary elements to change the input vector into its combined N-order value (take the second order as an example, such as the input parameters $X_1$ and $X_2$ in the multi-layer perceptron neural network, in the high-order neural network will become $X_1^2$, $X_2^2$, $X_1X_2$, $X_1^2$, $X_2^2$) (Figure 1). Compared with ordinary neural networks, it can improve the convergence speed and accuracy [8-10]. Specific explanation:

1. Improve the speed of convergence
   - The output of the network corresponds to the correlation function of the input, and the number of weight vector components also corresponds to the dimension of the input layer.
   - The weight vector components of ordinary neural networks are constantly changing, which makes the calculations more complicated. The output layer of the high-order neural network directly corresponds to the high-order correlation function of the input layer, and the number of weight vector components also corresponds to the dimension of the input layer, which reduces the computational complexity.
   - No hidden layer.
     - Ordinary neural network (such as BP) contains several hidden layers, which complicates the calculation. The high-order neural network has no hidden layer, which effectively improves the convergence speed.

2. Improve accuracy
   - Easy to achieve translation invariance, rotation invariance, and scale invariance.
     - In the calculation process of ordinary neural networks, the number of weight vector components is constantly changing, resulting in changes in translation, rotation, and scale, making the results inaccurate. The output layer of the high-order neural network directly corresponds to the correlation function of the input layer, and the number of weight vector components also corresponds to the dimension of the input layer. It is easy to realize the pattern recognition of translation invariance, rotation invariance, and scale invariance. Make the result more accurate.
   - Avoid falling into local minima
     - The weight coefficient of ordinary neural network depends on the first derivative information of the criterion function for correction. When there are multiple local minima in the solution space, once the randomly generated initial weight coefficient of the network is inappropriate, the network will fall into the local minima and cannot overflow. When the local extreme is small, the calculation ends, but the global optimal solution is not obtained. But after theoretical calculations, high-order neural networks can avoid this problem.

![General neural network model diagram (BP)](image1)

![High-order neural network model diagram (second-order)](image2)

Figure 1. Comparison of model diagrams of ordinary neural network and high-order neural network
(1) Normalize all data and determine training samples.
(2) Set the order of the neural network, convert the input samples, and input.
(3) Randomly set initial connection rights.
(4) Calculate the actual output.
(5) According to the error between the expected output and the actual output, update the connection weight and continuously train the network.
(6) When the network accuracy requirements are met, the training ends. Otherwise, it returns (5).

4. Practical Application

The PK area is located in China. A large set of semi-deep lake-deep lake system massive sandstone developed in the Triassic Yanchang Formation Chang 6 oil layer group in this area is a regional reservoir. Because it is located in the upper part of the Chang 7 source rock, it has a unique advantage of near-source hydrocarbon supply, and it contains huge potential for unconventional oil and gas resources. There are three types of sand bodies developed in Chang 6 deep-water sediments, namely sandy clastic flow sandbody, sandy landslide sandbody and turbidity current sandbody. After statistics of well data in the PK area, a total of 318 samples were obtained. Among them, 58 samples (including 22 samples of sandy clastic flow sand bodies, 11 samples of sandy slump sand bodies and 25 samples of turbidity current sand bodies) have the same evaluation results of $V_k, T_k, J_k, P_k$ and $D_k$. The remaining 260 The evaluation results of the samples are inconsistent. In order to ensure the applicability of high-order neural network heterogeneity evaluation methods in different types of sand bodies, 2, 2, and 3 were randomly selected from sandy clastic flow, sandy slumping and turbidity sand bodies. A total of 8 samples are used as test samples. The remaining 50 samples are used as training samples. The remaining 260 samples are used as prediction samples. After all data is standardized, different orders are set, and a high-order neural network model is established for training until the average network error $E_{ave} < Emin$, and the training ends.

$$E_{ave} = \frac{1}{n} \sum_{j=1}^{n} \frac{1}{2} (O_j - D_j)^2$$

Among them, $O$ is the actual output, $D$ is the expected output, $Emin$ is the network training accuracy, which is set to 0.003 here.

From the comparison table of heterogeneity accuracy of different orders of high-order neural network reservoirs (Table 1), it can be seen that with the increase of order, the accuracy is gradually improved. However, the increase of the order will reduce the calculation efficiency. For the consideration of the calculation efficiency and accuracy, it is believed that when the neural network is set to the 6th order, that is, when the average accuracy of all samples reaches 89.47%, it can meet the evaluation requirements of reservoir heterogeneity in the study area.

| Table 1. Comparison table of accuracy rate of high-order neural network evaluation of reservoir heterogeneity in the Chang 6 member of PK area |
|-----------------|---|---|---|---|---|---|---|---|
| Order           | 2  | 3  | 4  | 5  | 6  | 7  | 8  |
| Training samples (50) Average accuracy | 81.98% | 86.11% | 87.30% | 88.95% | 90.15% | 90.67% | 93.58% |
| Test samples (8) Average accuracy       | 81.36% | 80.74% | 85.12% | 86.46% | 88.79% | 87.66% | 91.23% |
| All samples (58) Average accuracy       | 81.67% | 83.43% | 86.21% | 87.71% | 89.47% | 89.16% | 92.41% |

Based on the evaluation results of 58 known samples, it can be seen that the evaluation range of the high-order neural network is 0~1. The closer the result is to 1, the stronger the heterogeneity of the reservoir. When the result is between 0~0.33, the heterogeneity is weak, when the result is between 0.33~0.66, the heterogeneity is moderate, when the result is between 0.66~0.93, the heterogeneity is strong, and when the result is above 0.93, the heterogeneity is very strong.
0.33~0.66, the heterogeneity is moderate, when the result is between 0.66~1, the heterogeneity is strong.

The above-trained model was used to comprehensively evaluate the remaining 260 samples, and the total 318 samples were classified into sand body genesis types for statistics (Table 2). It can be seen that the intralayer heterogeneity of different types of sand bodies is quite different. In comparison, the reservoir heterogeneity of sandy detrital flow sand bodies is the weakest, followed by sandy landslide sand bodies, and turbidity current sand bodies have the strongest heterogeneity.

**Table 2.** Evaluation parameters of reservoir heterogeneity of sandbodies of different origins in the Chang 6 member of PK area

| Sand body type                | Number of samples | High-order neural network reservoir heterogeneity evaluation results | Strength comparison of reservoir heterogeneity |
|------------------------------|-------------------|---------------------------------------------------------------------|-----------------------------------------------|
| Sandy detrital flow sand body| 136               | 0.132                                                               | weak                                          |
| Sandy landslide              | 62                | 0.485                                                               | medium                                        |
| Turbidity sand body          | 120               | 0.867                                                               | Strong                                        |

5. Conclusion
In this paper, a high-order neural network method is used to comprehensively evaluate the heterogeneity of the reservoir. The evaluation parameters include permeability variation coefficient, penetration coefficient, level difference, interlayer distribution frequency and interlayer distribution density. Effectively solve the problem of inconsistent conclusions on the evaluation of heterogeneity with the above single parameters. Unifying the comprehensive evaluation criteria of reservoir heterogeneity makes the evaluation results not only limited to the strength of heterogeneity, but also to quantitatively characterize its strength. Research on the heterogeneity of reservoirs in the PK area found that the heterogeneity of sandy clastic flow sand bodies is the weakest, the sandy landslide sand bodies are medium, and the turbidity current sand bodies have the strongest heterogeneity.

References

[1] Zhang Jie, Fang Feifei, Wang Jie, Tian Yajie, Mo Fei, Li Qi, Li Sainan, Huang Xiaoliang, Yang Yi, Liu Xue mei. Prediction of Intraformational Remaining Oil Distribution Based on Reservoir Heterogeneity: Application to the J-Field. Advances in Civil Engineering, 2021, 1-10.

[2] Liu Mingjie, Xiong Chen. Diagenesis and reservoir quality of deep-lacustrine sandy-debris-flow tight sandstones in Upper Triassic Yanchang Formation, Ordos Basin, China: Implications for reservoir heterogeneity and hydrocarbon accumulation. Journal of Petroleum Science and Engineering, 2021, 202.

[3] Yang Shaochun. A new method for quantitative research on reservoir heterogeneity. Journal of the University of Petroleum (Edition of Natural Science), 2000(01): 53-56. in Chinese.

[4] Iraj Parisa Tavoosi, Mehrabi Hamzeh, Rahimpour Bonab Hossain, Ranjbar Karami Rasoul. Quantitative analysis of geological attributes for reservoir heterogeneity assessment in carbonate sequences; a case from Permian–Triassic reservoirs of the Persian Gulf. Journal of Petroleum Science and Engineering, 2021(prepublish).

[5] Lv Yajuan. Study on Reservoir Heterogeneity of Putaohua Oil Layer in Gulongnan Area. IOP Conference Series: Earth and Environmental Science, 2021, 632(2).

[6] Yang Shaochun, Yang Zhaolin, Hu Hongbo. 2004. Entropy weight heterogeneous composite index algorithm and its application. Journal of the University of Petroleum (Edition of Natural Science), 28(1): 18–21. in Chinese.

[7] Liu Chao, Ma Kuiqian, Li Hongying, et al. 2012. Improvement and application of quantitative characterization of reservoir heterogeneity based on Lorentz curve method. China Offshore Oil & Gas, 24(02): 36-38. in Chinese.
[8] Zhilin Pu, Ruofeng Rao. LMI-based criterion on stochastic ISS property of delayed high-order neural networks with explicit gain functions and simply event-triggered mechanism. Neurocomputing, 2020, 377.

[9] Carlos Armenta, Thomas Laurain, Victor Estrada-Manzo, Miguel Bernal. A Novel Identification-Based Convex Control Scheme via Recurrent High-Order Neural Networks: An Application to the Internal Combustion Engine. Neural Processing Letters, 2020, 51(11).

[10] M. Hernandez-Gonzalez, M.V. Basin, E.A. Hernandez-Vargas. Discrete-time high-order neural network identifier trained with high-order sliding mode observer and unscented Kalman filter. Neurocomputing, 2019.