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Study on Damage Mechanism of Fracturing Fluid Reservoir and RBF Neural Network Prediction

Fei CHEN [a,b,1], Chaohui YAN[a] , Bo ZHOU[a]
[a] *Changqing Downhole Technology Company, Xi'an, Shaanxi,China*
[b] *CNPC Chuanqing Drilling Engineering Company Limited Xi'an, Shaanxi, China*

Abstract. At present, tight oil and gas reservoirs must adopt fracturing technology to obtain productivity, which will not only transform the reservoir, but also bring reservoir damage. Taking Chang-7 member of Ordos Basin as the research object, the relationship between physical properties of tight oil reservoir and fracturing fluid damage is analyzed based on experimental analysis of reservoir physical properties, cast thin sections, electron microscope scanning, X-ray diffraction and sensitivity test. Using the traditional damage evaluation method requires a large number of cores, and core resources, as a nonrenewable precious resource, have been paid more and more attention. Therefore, the use of prediction is conducive to protecting core resources, reducing experimental costs, and improving work efficiency. Therefore, a mathematical prediction model of RBF neural network is proposed, which establishes the complex nonlinear relationship between the physical properties of Chang 7 reservoir and fracturing fluid damage in Ordos Basin. Taking 22 groups of data of Chang 7 reservoir as training data, the fitting rate of training data is 90%. Taking the other two groups of data as detection data, the error between prediction and actual experiment is less than 10%. The prediction shows that the error inside and outside the sample predicted by RBF neural network is small, the prediction accuracy of the model is high, the generalization ability is strong, and the prediction value is closer to the value obtained by laboratory experiments than BP neural network, which can provide a good theoretical basis for fracturing fluid optimization.

Keywords. Fracturing fluid, Reservoir sensitivity, RBF Neural Network, Nonlinear relation

1. Introduction

Fracturing technology can significantly improve the productivity of a single well, and achieve the effect of increasing reserves and production. It is an essential technology for the development of low permeability and ultra-low permeability oil fields. The performance of fracturing fluid directly affects the fracturing performance and the uniform placement of proppant in the fracture, so fracturing fluid is one of the most important links in the fracturing process. At the same time, fracturing fluid will also cause damage to the formation, so the damage evaluation experiment should be carried out before the application of fracturing fluid, but the conventional evaluation time is

1 Corresponding Author, Fei CHEN, Nr. 12 Fengcheng 4th Road, West District, Xi'an City, Provincie Shaanxi, China; E-mail: 5430053@qq.com.

long, the cost is high, and the application of core resources is relatively large, which is increasingly unable to be met. People began to establish different empirical formulas, mathematical models, BP neural networks and other methods to predict the damage degree of fracturing fluid to the reservoir. Due to the accuracy of prediction and regional constraints, it is still unable to be applied on a large scale [1-8].

2. Reservoir Sensitivity

When a foreign liquid that does not match or does not match its own reservoir liquid enters the reservoir, its chemical and physical properties are inconsistent with the original liquid in the original reservoir, which will cause damage to the original clay minerals in the reservoir. Altered, reservoir damage from exogenous fluids occurs, so the sensitivity characteristics of the reservoir need to be analyzed. The potential sensitivity factors of the reservoir mainly include rock skeleton particles, pore structure characteristics, clay mineral types and their contents, and their own fluid properties. Among them, the changes of reservoir pore structure and their own fluid properties caused by external operations such as construction are external potential factors, and the types and contents of rock skeleton particles and clay minerals are internal potential factors. The analysis of potential sensitivity factors of the reservoir can be more purposeful Evaluate the sensitivity of the target formation more accurately, and the sensitivity of the reservoir directly affects the damage degree of the fracturing fluid and the optimization direction of the fracturing fluid.

Sensitive minerals refer to the sensitive minerals when the external conditions of the reservoir change. When external temperature, pressure, and fluid properties change, the physical and chemical properties of the minerals themselves change accordingly, which can lead to a decrease in reservoir permeability and affect the permeability of the reservoir. Clay minerals, non-clay minerals and formation granular minerals are all sensitive mineral.

3. Physical Properties of Reservoir

Through the content statistics of clastic components of rock samples, according to the triangle classification diagram method, it is concluded that the main rock type of Chang 7 reservoir in the study area is gray ~ dark gray fine-grained arkose, containing a small amount of lithic arkose (figure 1). According to the identification results of rock slices, feldspar in sandstone is the main mineral composition, quartz is the secondary, the content of rock debris is the least, and the content of biotite changes greatly, among which metamorphic rock debris is the main rock debris, followed by igneous rock and sedimentary rock debris. The heterobase is mainly argillaceous, with a content of 0 ~ 15.0%, and the average content is 3.4%; The cements are mainly carbonate minerals (5.5%), quartz enlargement (0.5%), feldspar enlargement (0.4%), and clay minerals (0.6%). According to the physical property data, the porosity of Chang 7 reservoir ranges from 1.18% to 16.40%, with an average of 7.12%; Permeability (0.01~5.77)mD, average 0.48mD. According to the distribution histogram of porosity and permeability, the main range of porosity of Chang 7 reservoir is 3% ~ 12%, accounting for 77.9% of the total samples, and the main range of permeability is (0.01 ~ 0.7)mD, accounting for 80.8% of the total number of samples. Mercury intrusion method is selected to study the characteristics of pore structure. Parameters characterizing pore throat size: displacement pressure reflects the concentration degree of rock pores and throats and the size of such pores and throats (Wang Yuncheng, 2004). The smaller the displacement pressure is, the better the physical properties of the reservoir are. The displacement pressure range of Chang 7 reservoir in the study area is 0.429 ~ 8.231 MPa, with an average of 3.938 MPa, and the maximum pore throat radius is 0.091 ~ 1.746 μm. Average 0.513 μm. The pore throat changes greatly. Cementation makes pores smaller, in which feldspar has undergone partial dissolution modification [9,10].

4. Physical Properties of Reservoir

RBF neural network is a forward network with three-layer structure: the first layer is the input layer, which contains many input nodes, and the number of input variables can determine the number of nodes; The middle layer is the hidden layer. Generally speaking, empirical formulas based on input layer and output layer are used. The number of counters in this layer is determined by the number of points, and the implicit elements in this layer use nonlinear transformation functions. The last layer is used as the response input data, that is, the output layer. Information can be transmitted between the first two layers. Similarly, information can also be transmitted between the latter two layers, while the input layer cannot pass the information directly to the last layer beyond the middle layer. The information transmission between the first two layers and the second two layers is different. The former is non-linear and the latter is linear.

Radial basis function (RBF) function is a scalar function with radial symmetry as the center. The usual definition is a monotonic function (because the distance is radial isotropic) that represents the radial distance (usually Euclidean distance) between the training sample and the data center. RBF is a commonly used kernel function. It is the most common kernel function in support vector machine model classification. Commonly used Gaussian radial basis functions:

$$K(x, x') = \exp\left[-\frac{\|x-x'\|}{2\sigma^2}\right] \ \gamma = -\frac{1}{2\sigma^2} \tag{1}$$

In the above formula, $\| x - x' \|$ can be regarded as the Euclidean distance of the square between two eigenvectors. X 'is the center of the kernel function, σ As a free parameter, it represents the width parameter, which is used to constrain the radial range of the function. An equivalent but simpler definition is to set a new parameter, whose expression is:

$$K(x, x') = \exp[\gamma \| x - x' \|] \tag{2}$$

Because the value of RBF kernel function becomes smaller and smaller with the decrease of distance, and its value is between 0 (limit) and 1 (when x=x '), it is a ready-made similarity measurement representation. The characteristic space of kernel has infinite dimensions; about σ = 1. Its expansion formula is:

$$\exp\left[-\frac{\|x-x'\|}{2\sigma^2}\right] = \sum_{j=0}^{\infty}\frac{(x^T x')^j}{j}\exp\left[-\frac{\|x\|_2^2}{2}\right]\exp\left[-\frac{\|x'\|_2^2}{2}\right] \tag{3}$$

The design idea of the network is as follows: RBF function is used to construct the space of hidden layer nodes, and the input parameters are directly mapped to the hidden layer space, so as to determine its basis function center. Because the signal between the hidden layer and the output layer of the network adopts the linear transmission mode, the output of the network can use the linear weighted sum of the output of its hidden layer nodes. The relationship between input layer and output layer in the network is a nonlinear mapping, and its output has a linear relationship with respect to variable parameters. Generally, linear equation or recursive least square method is used to solve it, so as to improve the weight of the network, improve the learning speed, and avoid the problem of falling into local minimum. The topology of the network is shown in the following figure 1.

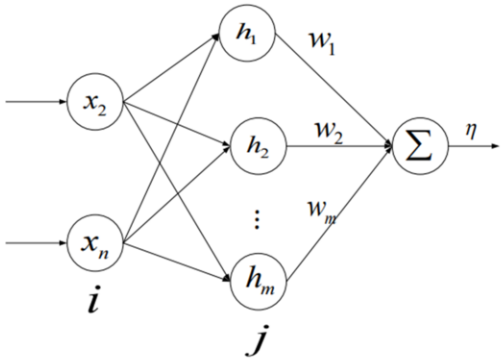


Figure 1. RBF network topology diagram

5. On Applications of RESERVOIR Sensitivity's Prediction

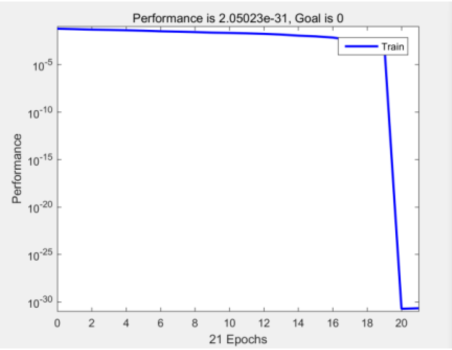
In order to improve the accuracy of the RBF neural network fracturing fluid damage model, it is necessary to replace a large number of samples for learning. The learning samples should correctly reflect the relationship between the input and output layers of the neural network. The above research shows that permeability, porosity, kaolinite, illite, chlorite, illite/montmorillonite interlayer, feldspar, quartz and fracturing fluid damage have nonlinear correlation. This time, the core analysis data of Chang 7 reservoir in B oilfield of Ordos Basin are selected, of which 23 sample data are used to study the model. The training shows that the result is stable after 20 iterations, as shown in figure 2. It shows that the training can fit the original data well, and the coincidence rate reaches more than 98%, achieving the expected effect.

Select another two sample data from other well areas to test the trained model and compare it with the data of indoor experiment, as shown in table 1. The prediction result is close to the real result, and the error of the prediction result is less than 5%. From the evaluation indicators, the error of RBF neural network is significantly smaller than BP neural network. Because RBF local approximation can simplify the calculation, its running time is also short. It is a prediction model for fracturing fluid damage [11].

Table 1. EXPERIMENTAL analysis sensitivity results and the corresponding parameters of samples

Muster	Input layer								Output layer
	K %	I %	C %	I/M %	Q %	F %	kf $10^{-3}\mu m^2$	Φ %	DR
1	9.0	38.0	8.0	45.0	35.0	54.0	27.5	14.0	0.2
2	13.0	37.0	9.0	41.0	44.0	36.0	1.8	7.7	0.6
3	3.0	75.0	9.0	13.0	40.0	42.0	0.2	8.5	0.6
4	10.1	34.6	7.4	47.9	43.0	46.0	2.4	11.2	0.7
5	33.9	23.8	6.0	33.8	32.0	35.0	2.4	13.4	0.0
6	10.0	0.0	0.0	90.0	42.0	28.0	0.2	8.0	0.8
7	23.0	26.0	13.0	36.0	43.0	26.0	3.1	10.5	0.8
8	0.0	67.5	0.0	32.5	44.0	40.0	1.3	9.2	0.5
9	0.0	32.0	0.8	67.3	55.0	36.0	0.1	7.4	0.4
10	70.3	0.0	29.8	0.0	44.0	30.0	0.3	2.0	0.0
11	72.4	0.0	27.6	0.0	44.0	30.0	11.1	2.1	0.5
12	26.3	22.8	6.2	43.4	29.0	32.0	53.1	18.8	0.5
13	83.0	6.0	0.0	11.0	54.0	31.0	3.7	12.7	0.4
14	74.7	13.5	8.8	3.0	51.0	40.0	1.7	11.6	0.5
15	14.5	47.0	10.8	27.7	29.5	50.4	10.7	12.3	0.3
16	42.5	26.0	11.0	40.5	34.0	59.0	0.5	4.8	0.2
17	66.0	9.0	8.0	16.0	52.0	46.0	0.5	8.9	0.4
18	4.3	2.0	1.1	0.6	40.0	39.0	15.7	16.3	0.0
19	10.0	45.0	31.0	13.0	30.0	15.0	3.1	11.2	0.5
20	75.0	0.0	0.0	25.0	36.0	26.0	2.7	14.2	0.7
21	65.3	9.3	17.8	7.7	84.0	12.0	0.6	20.5	0.7
22	9.0	43.2	8.0	45.0	43.2	32.7	27.5	16.0	0.6
23	13.0	37.0	9.0	41.0	43.5	33.1	1.81	7.7	0.7

(Φ:porosity, kf: permeability , I: illite, K: kaolinite, C: chlorite, Q: quartz, F:feldspar, I/M:illites/montmorillonite interstratified,DR:damage rate of water sensitive, DG: damage grade)



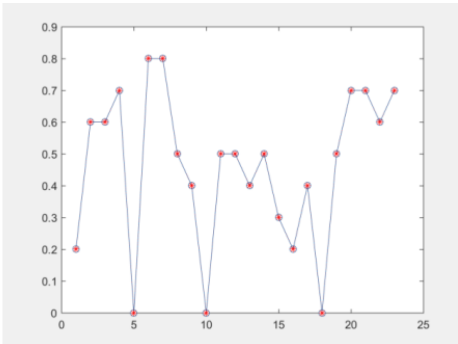


Figure 2. Cumulative iteration error and Training data

6. Conclusion

In order to predict the damage of fracturing fluid to the reservoir, based on the physical property data of the reservoir, 8 influencing factors including porosity, permeability and clay mineral value are selected for data mining. These indicators can comprehensively reflect the physical property of the reservoir.

A fracturing fluid damage prediction model based on RBF is established. Compared with BP prediction model, this model can approach any nonlinear function from any accuracy, has the characteristics of self-learning, self-adaptive and selforganization, and has strong prediction accuracy and generalization ability. It has certain advantages and reliability in predicting damage rate.

When building the RBF model, the relevant parameters (the center and width of the radial basis function, the weight from the hidden layer to the output layer) are three-layer. After 20 iterations, the result is stable, and the fitting degree of the original data exceeds 98%. In the future, the parameters that affect the prediction effect of RBF model can be optimized by combining particle swarm optimization algorithm, genetic algorithm, annealing algorithm and other optimization algorithms to avoid falling into local extreme value problem

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