Application of conventional logging interpretation fracture method based on neural network in offshore Oilfield L

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Abstract. The well data is required as a constraint for fracture prediction in the area. At present, imaging logging is considered to be the most accurate and effective means to interpret fractures, which can show the geological characteristics of the two-dimensional space of the borehole wall intuitively, vividly and clearly, but the experimental data is scarce due to the high cost of measurement. Conventional logging data are the main logging data in domestic oil and gas fields, so it is very important to use conventional logging data to effectively interpret fractures in the absence of drilling coring and imaging logging data. Based on the neural network algorithm, taking offshore Oilfield L in China as the application target, this paper optimizes the combination of conventional logging curves by establishing the nonlinear mapping relationship between the fracture strength curve and the conventional logging curve of sample wells with imaging logging data. By establishing the neural network model with nonlinear high learning ability for the optimized conventional logging curve and fracture strength curve, the fracture identification is carried out for the target interval of non-sample wells. The results show that this method can combine geology, geophysics, mathematics, computer and so on, and can effectively identify fractures in the study area. It has good adaptability to offshore fractured reservoir.

1. Introduction

For fractured dual medium reservoir, fracture is the main storage space and percolation channel of oil and gas. It is very important to accurately identify and describe fracture for exploration and development of dual medium reservoir. At present, fracture identification and evaluation mainly rely on drilling coring, imaging logging, conventional logging and other methods [1-3]. Although the drilling coring and imaging logging methods can show the main characteristics of fractures intuitively[4], there are generally problems of high measurement cost, especially for offshore oil fields with higher development investment, high test cost will significantly reduce the overall economic benefits of oilfield development, so it is difficult to obtain sufficient experimental data through these two methods. Identification of fractures by conventional logging method can reduce development investment to a certain extent, but there are some problems in the application of this method to identify fracture development, such as strong sample multi-resolution and low recognition accuracy[5]. In order to obtain relatively accurate results, a large number of sample collection and data analysis work are required, which reduces the work efficiency and is not conducive to efficient exploration and development of offshore oil fields. Because BP neural network method has the characteristics of...
flexible processing and analysis of data, it can rely on its sample learning algorithm to make up for the shortcomings of conventional methods such as limited statistical category and fuzzy processing results, so as to greatly improve the efficiency of fracture identification [6-9]. In this study, by establishing the nonlinear mapping relationship between the fracture strength curve and the conventional logging curve of the sample well with imaging logging, combining the methods of geology, geophysics, mathematics and computer, the neural network interpretation fracture method is innovatively applied to offshore Oilfield L in the South China Sea. The practice results show that the method can accurately identify and predict fractures, it has good adaptability to offshore fractured reservoir.

2. Principle of neural network
Neural network is a cutting-edge interdisciplinary subject, which is the most representative of machine learning technology [10-11]. It has the characteristics of autonomous learning, adaptive recognition, associative reasoning and so on. Among them, BP neural network is a kind of parallel structure network based on error back propagation algorithm, which has strong pattern recognition ability and learning ability and can simulate any nonlinear input-output relationship. The algorithm belongs to a typical multilayer feedforward network, which is composed of input layer, hidden layer and output layer. Most of the layers are fully connected, and there is no mutual connection between the elements of the same layer. In this algorithm, gradient descent method is used to realize fast convergence, so that the nonlinear mapping from N dimension to M dimension can be obtained. Its basic idea is to constantly adjust and modify the connection weight of the network through the back propagation of the network output error, so as to minimize the network error [12-15] (Figure 1).

![Figure 1. Schematic diagram of neural network.](image)

3. Fracture identification by conventional logging based on Neural Network
BP neural network is used to identify fractures from conventional logging curves by taking the logging information of sample wells as the input variable and the corresponding fracture strength curve as the output variable. Through the neural network system with nonlinear high learning ability and specific algorithm, the mapping relationship between each well logging curve and the corresponding fracture strength can be obtained. Then the fracture identification of the target interval of the unknown well is carried out through this mapping relationship.

There are four parts in conventional logging fracture identification based on neural network, which are collecting learning samples, establishing neural network relationship, method verification and fracture interpretation. Firstly, the wells with drilling core or imaging logging interpretation in the study area are collected as sample wells. According to the core analysis and imaging logging interpretation, the fractures of sample wells can be effectively identified and the fracture strength curve of sample wells can be generated. Secondly, the neural network relationship is established to
optimize the conventional logging curve with good correlation with fracture strength curve. Fractures are reflected in many conventional logging curves. The logging response characteristics of fractures are affected by many factors such as fracture development degree, occurrence, opening, extension length, etc., so the response characteristics of fractures in each logging curve are also different in different blocks. The purpose of logging optimization is to find out the curves sensitive to fracture development in a given block. The specific method is to establish the neural network relationship between the conventional logging curve and the fracture strength curve of the sample well, analyze the characteristic response of the fractures in this block on the conventional logging curve, and select the logging curve that is more sensitive to the fracture response as the conventional logging curve for fracture prediction and identification. Thirdly, the neural network model between the Optimized conventional logging curve and fracture strength curve is established. The strength curve of any sample well is inferred by the model, and the result is compared with the actual strength curve to achieve the purpose of verification. Finally, the fracture strength curve and fracture development section of non-sample wells are inferred by the neural network model, and carry out dynamic verification for fracture prediction of non-sample wells (Figure 2).

Figure 2. Flow chart of conventional logging interpretation fracture method based on Neural Network.

4. Example application

4.1. Overview of offshore Oilfield L
Offshore Oilfield L is located in the south of Dongsha uplift. The main development layer is biothermal beach limestone of the upper Tertiary Pearl River formation. It is a massive bottom water reservoir with a uniform oil-water interface. The thickness of the oil layer is large and the buried depth is 1198-1273m. The work area belongs to the platform margin sedimentary subfacies of carbonate platform facies, including three kinds of sedimentary microfacies: Reef, debris beach and mud mound. The reservoir belongs to medium high porosity and permeability reservoir, and its physical properties change greatly in vertical direction. The reservoir types are mainly pore type and cave pore type. The
fractures in this block are mainly structural fractures, accompanied by normal fault development[16], and the strike of fractures is mainly from northwest to Southeast, with small scale, density and length.

4.2. Fracture identification of sample wells and logging curve optimization
The well logging curve of offshore Oilfield L is standardized. Through the curve filtering, the statistical fluctuation and burr interference irrelevant to the formation properties are filtered out, and only the useful components reflecting the formation characteristics on the curve are retained, so as to eliminate the impact of environmental factors such as borehole and mud invasion.

The well with imaging logging data in offshore Oilfield L is selected as the sample well of the oilfield. The fracture strength curve is generated by interpolation of the imaging logging interpretation fracture data of the sample well, and the fracture development section of the sample well is divided according to the fracture strength curve.

The conventional logging curve of offshore Oilfield L has different responses to fractures, such as the separation of deep and shallow lateral resistivity; the sudden decrease of density; the slightly higher gamma value in the background of low amplitude; the cycle jump of acoustic time difference sometimes reflects the existence of low angle fractures. However, due to the influence of other factors such as fillings, mud, dissolution and so on, the effectiveness of single conventional logging is not enough to make it a reliable data resource for fracture reservoir evaluation. By establishing the neural network model of sample wells in the study area, the conventional curve combination with good correlation with fracture strength curve is selected for neural network operation. The results show that in the sample well, the curve combination of gamma curve, density curve and acoustic time difference curve has a good correlation with the fracture strength curve, with a total correlation of 0.7622 (Figure 3). Then the neural network model based on the optimized conventional logging curve and fracture strength curve can be used to predict the fracture development of non sample wells.

|          | GR   | RHO B | DT   | Intensity |
|----------|------|-------|------|-----------|
| GR       | 1.0000 | 0.0407 | 0.0604 | 0.2415    |
| RHO B    | 0.1407 | 1.0000 | 0.9961 | 0.6742    |
| DT       | 0.1604 | 0.9961 | 1.0000 | 0.6804    |
| Total    | 0.3284 | 0.9963 | 0.9963 | 0.7622    |

Figure 3. Statistical table of correlation between fracture strength curve and conventional curve in offshore Oilfield L.

4.3. Method validation
The neural network relationship between the fracture strength curve and the optimized conventional curve is established in two of the three sample wells to calculate the strength curve of the third sample well, and the result is compared with the actual fracture strength curve. As shown in Figure 4, the first curve is the fracture strength curve predicted according to this method, the second curve is the actual fracture strength curve generated by interpolation of fracture data interpreted by imaging logging, and the rest are fracture parameter data interpreted by imaging logging. The results show that in three sample wells, the predicted strength curve with 0.1 as the boundary value (in the yellow part of Figure 4) can better reflect the fracture development section, the predicted strength curve has a high correlation with the actual strength curve, and the matching degree is more than 80%, which shows that the method is feasible.
4.4. Fracture prediction and dynamic verification of non sample wells

Based on the cross validation of each sample well with the neural network model, the fracture strength curve of the remaining wells in offshore Oilfield L is inferred by this method, and the fracture development of single wells in vertical wells and horizontal wells in the whole area is explained. As shown in Figure 5, the curve is the predicted fracture strength curve, with 0.1 as the boundary value, the fracture development section of single well is divided according to the curve.

There are 20 wells predicted in the study area, which can be divided into two categories according to the fracture development. The fracture of the first kind of well is relatively developed, with fracture development intensity of 0.4-1. At the initial stage of production, the daily production of this kind of wells is relatively high, the daily liquid production is usually more than 800m³, and the water cut rises rapidly, usually from low water cut stage to high water cut within two years. The second type of well
has low fracture development degree and fracture development intensity of 0.2-0.4. The daily production of liquid and oil is relatively low at the initial stage of production, and the water cut rise rate is relatively slow, from low water cut stage to high water cut stage usually need more than two years. As shown in Table 1, the dynamic response characteristics of 17 predicted wells are consistent with the interpretation of fractures, with a coincidence rate of 85%.

Table 1. Fracture interpretation and dynamic characteristics compliance of prediction wells.

| Fracture development type of prediction well | Well name | Starting date for production | Production horizon | Initial stage of production | Water cut rising speed | Compliance of interpreted fracture |
|---------------------------------------------|-----------|------------------------------|--------------------|-----------------------------|------------------------|------------------------------------|
| Class I: fracture development, fracture development strength 0.4-1 | X1 | 1996/4/29 | B1 | 909.8 | 881.3 | 3.1 | fast | √ |
| X2 | 1996/3/29 | B1 | 1108.1 | 1024.6 | 7.5 | fast | √ |
| X3 | 1996/4/3 | B1 | 885.9 | 825.8 | 6.8 | fast | √ |
| X4 | 1996/3/29 | B1 | 1106.6 | 1056.5 | 4.5 | fast | √ |
| X5 | 1996/11/21 | B1 | 1082.8 | 877.9 | 18.9 | fast | √ |
| X6 | 1996/4/3 | B1 | 916.9 | 844.6 | 7.9 | fast | √ |
| X7 | 1996/4/3 | B1 | 1233.8 | 1131.8 | 8.3 | fast | √ |
| X8 | 1996/4/20 | B1 | 1092.0 | 872.5 | 20.1 | fast | √ |
| X9 | 2004/7/4 | B1 | 896.6 | 800.4 | 10.7 | fast | √ |
| X10 | 1996/3/29 | B1 | 866.3 | 849.8 | 1.9 | fast | √ |
| X11 | 1996/3/29 | B1 | 1113.0 | 1057.0 | 5.0 | fast | √ |
| X12 | 1996/9/26 | B2 | 1134.8 | 636.0 | 44.0 | fast | √ |
| X13 | 1996/9/14 | B2 | 1219.3 | 930.7 | 23.7 | fast | √ |
| X14 | 2001/7/13 | D | 1999.1 | 15.7 | 99.2 | Unable to judge relatively slow | × |
| X15 | 1996/8/6 | B3 | 1526.9 | 1009.2 | 33.9 | relatively slow | √ |
| X16 | 1996/7/17 | B1 | 998.8 | 937.5 | 6.1 | relatively slow | × |

| Class II: the fracture degree is relatively low, and the intensity is 0.2-0.4 | X17 | 2004/5/1 | B1 | 541.1 | 522.8 | 3.4 | relatively slow | √ |
| X18 | 2003/6/30 | B1 | 476.6 | 463.0 | 2.8 | relatively slow | √ |
| X19 | 2005/2/17 | B1 | 537.2 | 461.4 | 14.1 | relatively slow | √ |
| X20 | 2005/12/27 | B1 | 567.2 | 446.2 | 21.3 | relatively slow | √ |

5. Conclusion

Some concluding remarks of the present study are briefly explained as:

1. The conventional logging interpretation of single well fracture based on neural network technology is a relatively low cost and effective fracture identification and evaluation method, which is of great significance in the case of limited imaging logging data and core samples.

2. In the process of using neural network to interpret fractures from conventional logging curves, the key is the optimization of logging curves and the verification of neural network model. The neural network training model is used to realize the highly nonlinear mapping between the input factors and the output targets, and the logging curve which can best reflect the fracture development in this area is optimized. At the same time, the neural network model is verified to improve the interpretation accuracy of the fracture development of non sample wells.

3. The application practice of offshore Oilfield L in the South China Sea shows that the fracture interpretation of single well is carried out by using the conventional logging interpretation method based on neural network, the result of fracture interpretation is highly matched with the actual, and the effect is good. It has good adaptability in offshore oil fields, so this method can be widely used.
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