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Waterflooding identification of continental clastic reservoirs based on neural network

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ABSTRACT: This article describes an approach based on artificial neural network to identify waterflooded zone of continental clastic reservoirs. For the logging sequence of waterflooded zone matching the characteristics of the continental oilfield, the application of artificial neural network algorithm is able to distinguish water layers, oil reservoirs and dry layers among reservoirs of waterflooded zones. The output vectors of the network represent the fluid types. Thus, better results are supposed to be obtained than traditional methods in the crossplot plate after network training. Distribution becoming non-uniform and contact between grains being loose were found after microscopic observation in the waterflooded zones. It has revealed that the waterflooded characteristics are of great significance, and it has also proved the accuracy of identification from another perspective.

KEYWORDS: Waterflooding, continental reservoirs, neural network, identification, fluid.

1 INTRODUCTION

Most oilfields in China belong to continental deposition. Because of strong reservoir heterogeneity and lacking of natural energy, water injection exploitation has been widely used. China is also one of the countries with the highest proportion of waterflooding oilfields in the world [1]. High complexity of waterflooded reservoirs and uncertainty of remaining oil distribution have made oilfield development become more and more difficult. In the current situation, the understanding of waterflooded condition has become a very important and urgent issue in oilfield development. It also has a positive significance on tapping the potential synergies work at high water cut stage. However, traditional methods on waterflooding identification have limited applications due to the identification accuracy rate of less than 50 percent [2].

By considering the identification accuracy, neural network integrated multi-logging information was brought in to achieve better results in quantitative identification. In the past 20 years, neural network technology has been used in petroleum exploration and development, including reservoir rock properties [3], lithology [4,5], porosity and permeability [6,7,8], and flow units [9] estimation.

This article aims at describing waterflooding identification of continental clastic reservoirs in China based on the back-propagation neural network. As a new information processing technology, the neural network approach has a broad application prospect. Moreover, this method has several advantages over traditional methods in identification accuracy rate.

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2 METHODS

2.1 THE CHOICE OF INPUT AND OUTPUT VECTORS

Logging curves corresponding to the testing data that determine the oil and water layer is the input vector of the network training. Several well logs are selected from the existing well log data for the network input and these log curves basically reflect the lithological and electrical characteristics of the waterflooded reservoirs. Before neural network training, log curves must be normalized to make their values between 0 and 1.

Types of reservoir fluid are the neural network training target vectors. Digital processing is done on the target vectors corresponding to the types of fluid, in order to facilitate the project on the two-dimension corresponding system. The output code of oil reservoir is set as (0.25, 0.25), dry layer as (0.25, 0.75), waterflooded zone as (0.75, 0.25) and water layer as (0.75, 0.75).

2.2 THE CHOICE OF NETWORK STRUCTURE PARAMETERS

The back-propagation neural network is a network of multi-level structure with the input layer corresponding to the well logs and the output layer corresponding to the fluid type.

However, the middle layer has no uniform standard selection. When each node uses the S-shaped activation function, a middle layer can be achieved for the classification of any judgment.

2.3 NETWORK TRAINING

Using of BP neural network algorithm, appropriate weights and threshold values are selected to build the network model and used for model training and error testing.

The neural network training is carried out against the known input vectors and target vectors. The various parameters of the network are identified after the success of online learning.

Thus, a crossplot plate for identifying oil reservoir, dry layer, waterflooded zone and water layer is created.

The key to identify fluid type based on BP neural network algorithm is to choose high-quality well logs, oil test data and network structure parameters. Based on BP neural network, a simulation crossplot plate applying to continental clastic reservoir development is designed in this study that can be used to identify oil reservoirs, water layers, dry layers and waterflooded zones in continental oilfields (Fig.1).

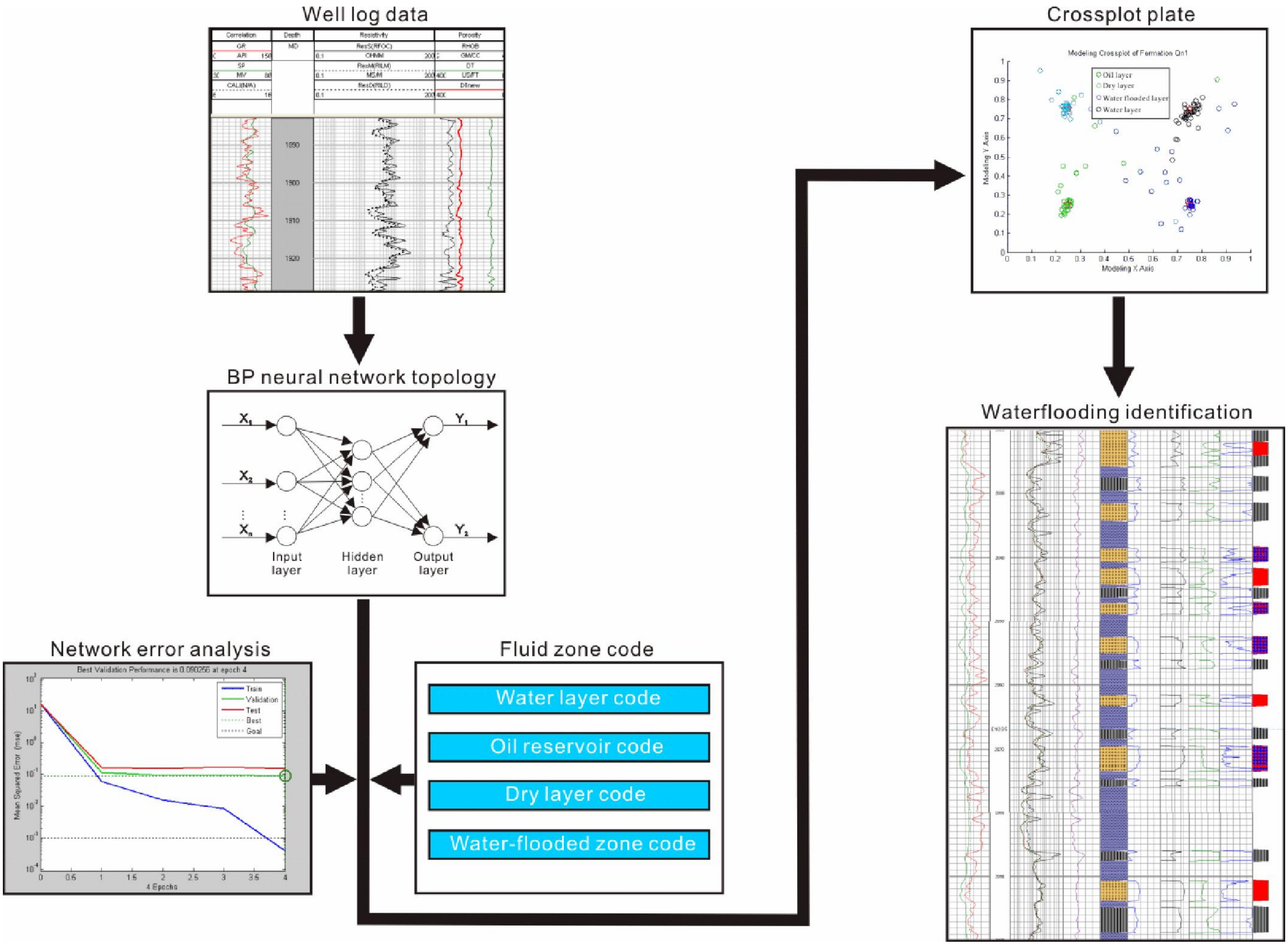

Fig. 1. Simplified workflow showing the key components of the approach of the waterflooding identification with an artificial intelligence tool (neural network)

3 RESULTS

Due to different sedimentary characteristics of each continental oilfield, there are various waterflooding characteristics. Gaoji Oilfield in Subei Basin of east China is taken as an example to describe this methodology.

Five well logs (GR, DT, RFOC, RILD, and RILM) are selected as the input to the network in the water flooding study of Gaoji Oilfield. The input and output vectors are initialized for 5-dimensional and two-dimensional respectively to build the BP neural network model, applying the unique non-linear mapping features of the neural network. After adding fluid zone code and doing network error analysis, the training is ended by superimposing the network output values and the oil production conclusions. Of course, the process of network error analysis should be continued until it meets the waterflooded identification accuracy.

Thus, a crossplot plate is acquired that can predict waterflooded reservoirs in the Funing Formation of Gaoji Oilfield. As a result, we obtain the distribution of the recognition results on the crossplot plate, achieving the entire prediction process.

Through the projection points of identification vectors on the network output, Euclidean distance is used to determine the distance between the centers of these distribution points with the fluid types. The shortest distance from the center of the depth of segment reservoir fluid type represents the fluid type. The log curve values of sandstone sections that can identify fluid type are input, and the waterflooded zones of each well are found.

Using the method discussed previously, 11% of the data is selected to enter into the crossplot plate which is trained by another 89% of the data. Prediction accuracy rate of the network is up to 85% by comparing the oil production test conclusions and neural network recognition results. It proves that neural network acts as a good and useful tool from well logs to predict waterflooded reservoirs. It should be noted that we should avoid the proportion of samples of the same characteristics being too large, resulting in the so-called over-learning.

4 Discussion

A neural network crossplot plate for waterflooded reservoirs identification is set up, and the identification accuracy rate is ideal [10]. The neural network demonstrates the superiority of its information processing and achieves automatic processing and interpretation of logging data. It has the guidance of the general method for the identification of a variety of fluid types. And it has been already widely used in multiple fault-blocks in Gaoji Oilfield, Pucheng Oilfield, Weicheng Oilfield, Wenmingzhai Oilfield et al.

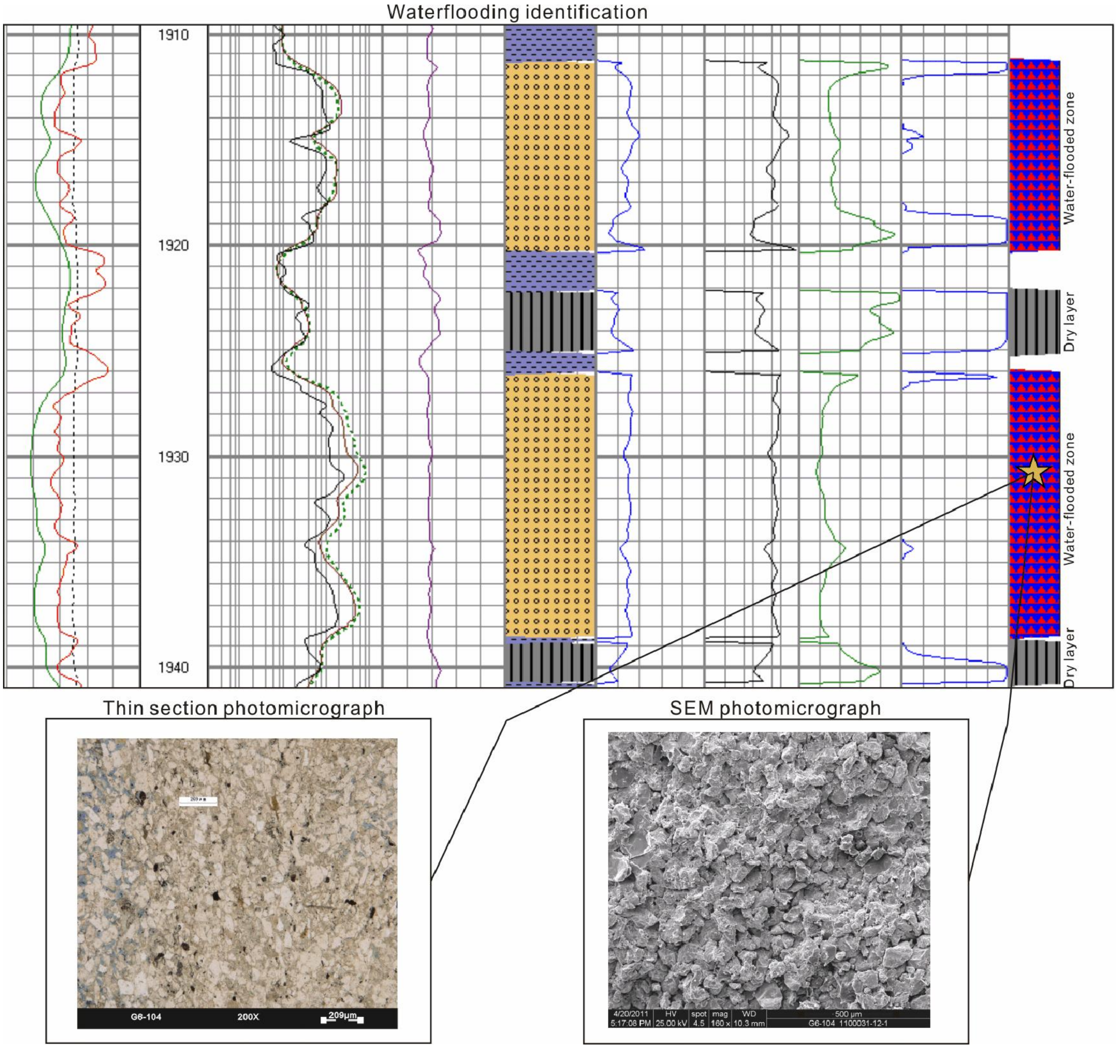

Fig. 2. Waterflooding identification of the well G6-104 of Gao 6 fault-block in gaoji oilfield and photomicrographs of the waterflooded zones

Traditional methods of analyzing water flooded characteristics tend to focus on reservoir characteristics of one or a limited number of areas, which often leads to some exceptions phenomena or disturbances. Besides, it rarely involves microscopic comparative analysis, which is not conductive to explore regular pattern of reservoirs before and after water flooding. Thin section and SEM photomicrographs indicate that contact between grains of the waterflooded zone is looser, with secondary intergranular pores relatively developed. At the same time, local pore distribution is uneven. Waterflooding development causes major changes in the microscopic pore structure, which determines fluid flow and hydrocarbon migration and accumulation of the micro-pores. Microscopic phenomena of the photomicrographs show strong waterflooded characteristics (Fig. 2). Meanwhile, we should clarify changes of the common cement constituents in the study area, whether they are carbonate cements or clay minerals.

A comprehensive analysis of parameter variations, such as physical properties, pore structure, formation water salinity, oil saturation, and reservoir oil viscosity are used to conduct based on the waterflooded identification. Thus, a system parameter comparison method is formed from a multi-angle between macro and micro (Fig. 3).

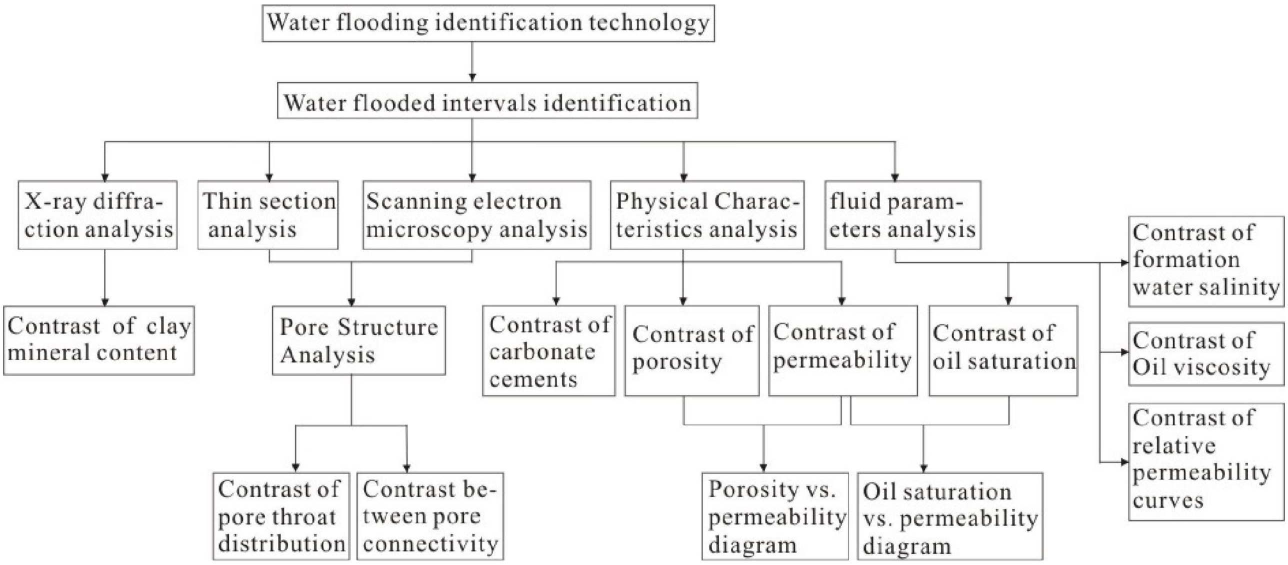

Fig. 3. Pathways of a system parameter comparison method based on the water flooding identification technology

On the basis of waterflooding identification during the development process of the continental oilfield, analyzing the changes in characteristic parameters of the waterflooded reservoirs helps to summarize the waterflooding regularity. The characteristic parameters are due to oilfields, there is no universal adaptability. It is normal that anomaly regularity phenomenon in certain oilfield. Reservoir heterogeneity has a strong control of the waterflooding regularity [11]. However, the method is generic, and each oilfield can analyze and summarize waterflooding regularity of its own to guide the production.

A proper understanding of the waterflooding situation and grasping the flooding of regularity can further provide guidance of remaining oil, so that the development of adjustment will achieve the best results. Therefore, semi-quantitative to quantitative evaluation is needed to perform after determining the specific waterflooded zones. Interpretation models of log parameters could be established, including porosity, permeability, shale contents, water (oil) saturation, and moisture contents. By establishing the interpretation models, especially the model of moisture contents (Mc), we can determine the level of water flooding. And the level of waterflooding is divided as follows: (1) oil reservoir: Mc<10%; (2) weak waterflooded zone: 10%<Mc<40%; (3) medium waterflooded zone: 40%<Mc<80%; (4) strong waterflooded zone: Mc>80%.

Further development of the fine interpretation of the waterflooded zone could be carried out on the basis of waterflooding identification to increase the recoverable reserves of the continental oilfield. Using neural network technology for logging analysis to provides a new means of interpretation of waterflooding, so as to serve further reservoir distribution and dynamic monitoring.

5 CONCLUSIONS

(1) In this study, a back-propagation neural network consisting of the combination of well logs and the fluid zone codes are used to estimate waterflooded zone. The network is trained to adjust the network weights and thresholds according to the network prediction error to minimize the network error. Excellent correlation is acquired between the network output values and the oil production conclusions after training. And it also further validates the accuracy of the neural network algorithm, utilizing well logs combination perfectly. Thus, a crossplot plate is acquired to identify waterflooded reservoirs in the study area.

(2) Combining characteristics of continental oilfields, it is necessary to produce different types of crossplot plates in different blocks or oilfields. It also helps to carry out fine interpretation of the waterflooded zones and to ensure high and stable production of oilfields.

(3) Based on the waterflooding identification, in-depth analysis of the waterflooded characteristic will help to master the waterflooding rules, and to further improve the waterflooding identification system.

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