

Research on Water Finding Methods for Horizontal Wells

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Abstract: The outflow of water from horizontal wells will lead to a decrease in oil production and a decrease in production efficiency. The commonly used water exploration methods have problems such as harmful oil layers, long auxiliary logging time, low efficiency, high cost, and discontinuous testing data. The technology of using crawlers to lower and search for water does not require the cooperation of the operation team. Logging work can be carried out during mining, and real-time monitoring of the production well can be carried out. The instrument is kept in the center of the casing, with high testing accuracy and short logging time, which improves production efficiency. In response to the problem of difficulty in locating the water outlet position using the crawling water finding technology, this article establishes a method for determining the water outlet position of a horizontal well based on the actual working conditions of a domestic oil field using the crawling water finding technology.

Keywords: Horizontal Well Water Finding Technology; CFD Fluid Simulation; BP Neural Network.

1. Introduction

All Horizontal well technology is an important technology to realize the growth of recovery in old oilfields and low-permeability reservoirs as well as the more efficient development of new oilfields with fewer wells, which has been widely emphasized and applied on a large scale worldwide, and has achieved outstanding economic and social benefits. Since the 1990s, the research and development on horizontal well development technology has developed very rapidly [1], and it has been widely applied in the development of oil and gas reservoirs such as bottom-side water, natural fracture development, thin layer, low permeability, unconventional, and conventional thick oil, which has become a new type of development method, and it is an important means to change the traditional open method. In the development history of horizontal well technology, it has mainly experienced five technological changes: in 1920-1930, the breakthrough of reflection seismic technology promoted the progress of horizontal well development, and the production increased from 1×10^8 t to 2×10^8 t; in 1960-1970, with the development of oil production theory, injection drilling, water injection development, plate tectonics and other technologies[2], it promoted the production of horizontal wells from 10×10^8 t to 20×10^8 t. 10^8 t to 20×10^8 t; in 1980-1990, relying on the development of basin simulation,

secondary oil recovery technology, 3D seismic, and horizontal drilling, horizontal well production was maintained at around 30×10^8 t; in 2000-2015, unification was shown in the technologies of ultra-high-density data acquisition, drilling logging with drilling, horizontal well fracturing in sections, and rotary-guided drilling, with the production stepping up to 40×10^8 t ; in 2020-2035, it will be represented by new technologies such as intelligent drilling, intelligent oilfield, in-situ reforming, nano oil drive, etc., which may drive the production to cross a new high[3].

This paper takes horizontal well water search as the engineering background, through a large amount of data collection and literature exploration, carries out the theoretical research on horizontal well water search, on the basis of which it carries out the indoor simulation experiment of oil-water two-phase flow, obtains the water content rate of each monitoring point, and then compares it with the experiment by means of CFD fluid simulation and constructs the BP neural network model, predicts the location of the water outlet point.

2. Numerical Simulation of Multiphase Flow in Horizontal Wells

2.1. Computational Model

2.1.1. Model

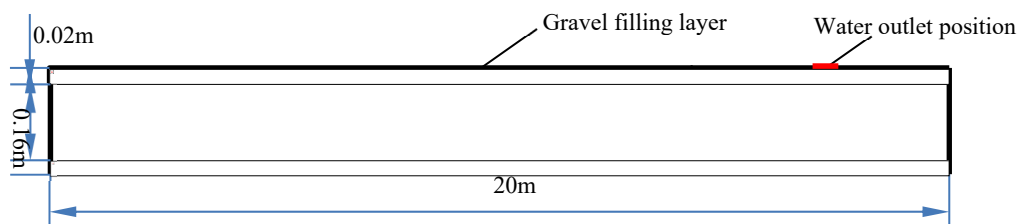


Fig 1. computational area

The horizontal well water finding calculation model is shown in Fig1. Assuming that the diameter of the borehole is

0.2m, the thickness of the filler layer and screen tube is 0.02m, the diameter of the casing is 0.16m, and a 20m long pipe

section is taken for the study. The location of water outlet is 2m away from the wellhead on the right side of the screen tube, taking the right side of the wellhead as the inlet of the mixture, and the wellbore as the penetration of the screen tube

into the oil-water mixture.

2.1.2. Boundary Condition

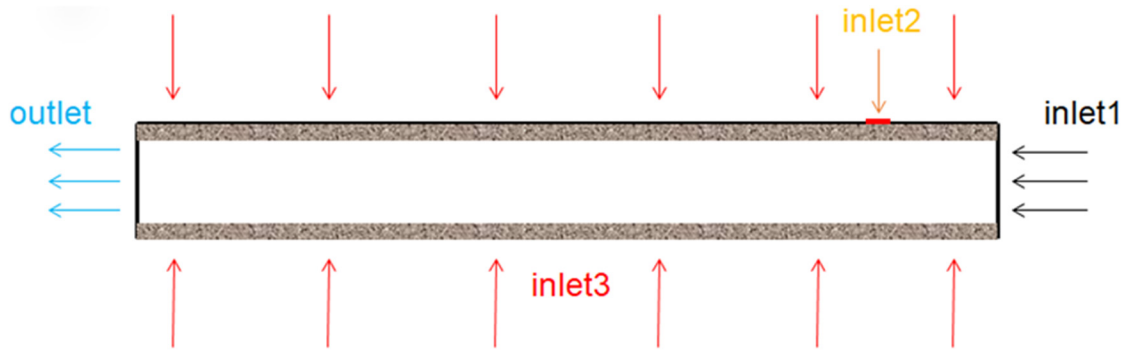


Fig 2. Boundary conditions (inlet, outlet)

Define the right wellhead as the wellhead mixed fluid flow inlet inlet1, set it as velocity inlet, calculated through the pipe diameter and flow rate of the inlet and outlet velocity of 0.11764m/s, of which the oil phase accounts for 30%, the water phase accounts for 70%; set the location of the outlet as the velocity inlet inlet2, with the velocity size of 0.12053m/s, and the water phase accounted for 100%; the sieve tube slit as the velocity inlet inlet3, the velocity size is set to 0.02913m/s, the oil phase accounts for 30%, the water phase accounts for 70%; the left wellhead is the outlet, set as the pressure outlet. Referring to the relevant well condition data in the field, the temperature is set to 75°C, the viscosity of crude oil is set to 3.32mPa-s, the density of crude oil is set to 863kg/m³, and the average pressure of the formation is taken to be 6.43MPa. Define the horizontal section of the wellbore as a wall, and adopt the no-slip boundary condition.

Due to the oil-water two-phase flow simulation model studied in this paper, and the mesh is structured, in order to ensure the accuracy of the calculation results, this paper adopts “PRESTO!” as the pressure interpolation scheme, and the numerical simulation is thus carried out [4].

The computational model used in this paper is a steady state flow model and hence the Coupled algorithm is used in this paper [5].

The standard k-ε model shows better numerical stability and has better descriptive ability for the turbulence structure and turbulent energy transfer of the flow, and it is proposed to select the standard k-ε model as the turbulence model in this paper [6].

2.2. Grid Segmentation and Irrelevance Verification

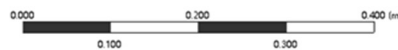
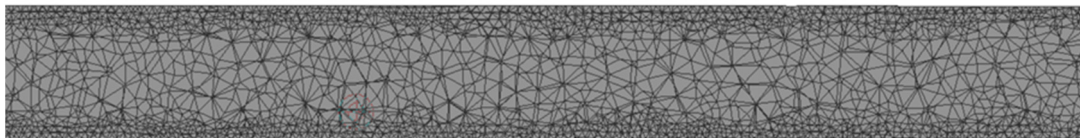


Fig 3. Lattices

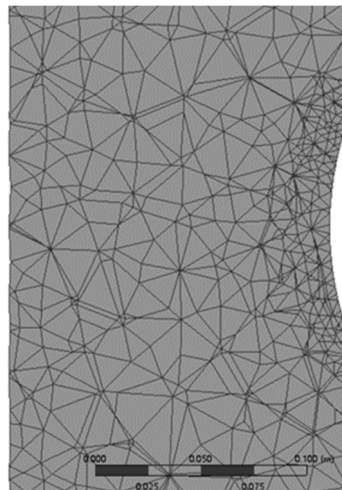


Fig 4. Localized encrypted grids

In pre-processing meshing, MESH is selected for grid generation. Firstly, the mesh is generated for the fluid domain formed by the horizontal well pipe, outlet, and screen pipe slit. Aiming at the relatively simple situation of fluid flow in the horizontal well bore, a structured triangular mesh is chosen for mesh discretization. Due to the complexity of the structure of the sieve tube gap and the outlet, it is necessary to encrypt the mesh of these two structures, so as to reduce the mesh size, increase the number of meshes, and improve the accuracy of the calculation. As shown in Fig. 3 is the flow field mesh delineation profile of the horizontal wellbore in the Y-Z plane; the local enlargement of the encrypted part at the outlet location of the horizontal well is shown in Fig. 4. In this project, a structured grid is used, with the grid size set to 0.02 m. The grid encryption is applied to the screen tube gap and outlet location, and the number of generated grids is about

1,320,000, which generates about 270,000 nodes, and the mesh irrelevance validation verifies that the influence of this magnitude of grid on the simulation results is negligible.

This project takes the horizontal section of horizontal wells as the research object, obtains the calculation model with different grid numbers by changing the scale of grid division of flow field in the horizontal section of horizontal wells, sets the same boundary conditions and operation parameters, and monitors the water content at the outlet of the horizontal section, and the results are shown in Table 1, which indicate that the influence of the number of grids on the calculation results is negligible when the number of grids is more than 1.1 million, and meanwhile, in order to ensure the calculation accuracy, the This project intends to select the more reasonable 1.3 million grid as the subsequent grid division guidelines.

Table 1. Monitoring data for different grid quantities

Number of grids (ten thousand)	90	110	130	150	170
Water content at the outlet	84.8629%	84.8733%	84.8739%	84.8742%	84.8740%

2.3. Analysis of Simulation Results

Analyze the distribution of water content within the wellbore. The volume distribution cloud maps of oil and

water phases in the horizontal wellbore of a horizontal well were obtained using computational fluid dynamics methods, as shown in Figures 5 and 6.

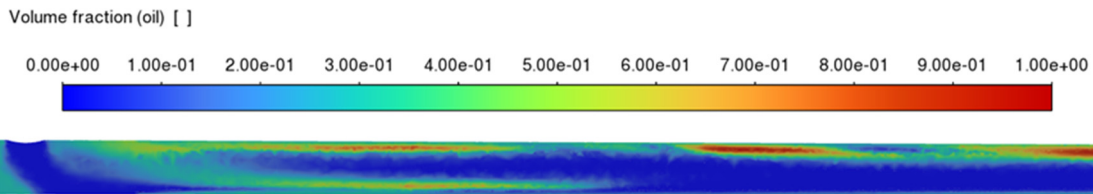


Fig 5. Oil phase volume fraction distribution cloud map

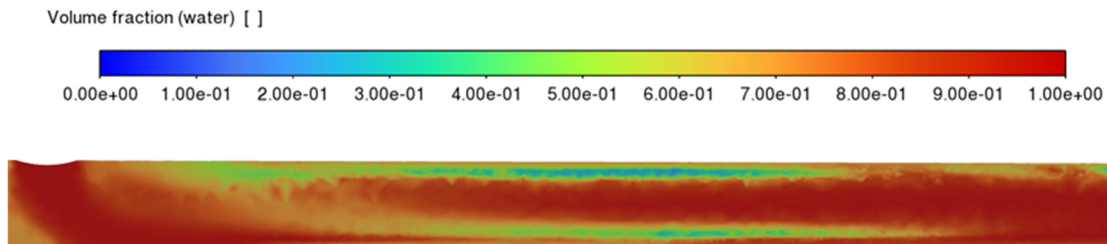


Fig 6. Cloud map of water phase volume fraction distribution

From the distribution cloud map of volume fraction, it can be seen that during the oil recovery process, due to the light density and low viscosity of oil, it often floats up to higher positions, while water has a heavy density and high viscosity, and often sinks to lower positions. This forms a stratification phenomenon between the oil layer and the water layer, where the oil layer is located in the upper part and the water layer is located in the lower part. Therefore, the oil-water mixture undergoes flow stratification after passing through the outlet position for a certain distance, which is consistent with the actual working conditions.

Obtain water content data from various monitoring points, as shown in Table 2. The water content of horizontal wells gradually decreased from 84.87% to 74.35%.

Table 2. Water content data of each monitoring point

spacing(m)	Moisture content (%)
0	84.87%
1	83.93%
2	80.35%
3	78.87%
4	78.38%
5	77.25%
6	75.60%
7	75.18%
8	75.08%
9	74.60%
10	74.35%

3. Horizontal Well Water Output Prediction

After the construction of the wellbore water content database is completed, data mining methods can be used to obtain the distance between the water outlet position and the monitoring instrument [7].

Assuming the water outlet is located at point P₁, a monitoring point is set every 1 meter, consisting of 16 points from P₁ to P₁₆. If the crawler is located at point P₁, the water content measured at point P₉ can be used as its outlet water

content. The mixed liquid flow rate in the wellbore, gravel filling porosity, and other related information can be measured. Then, the water content of each monitoring point in P₁-P₈ is measured, and the corresponding water content row in the database is searched. Then, the water content value closest to the water content of the 8 measuring points in P₁-P₈ is searched, and the corresponding position in the database is the predicted water outlet point.

By analogy, when P₂ is used as the current point, P₁₀ is the outlet moisture content, and the database is searched in the same way to obtain the most matching position.

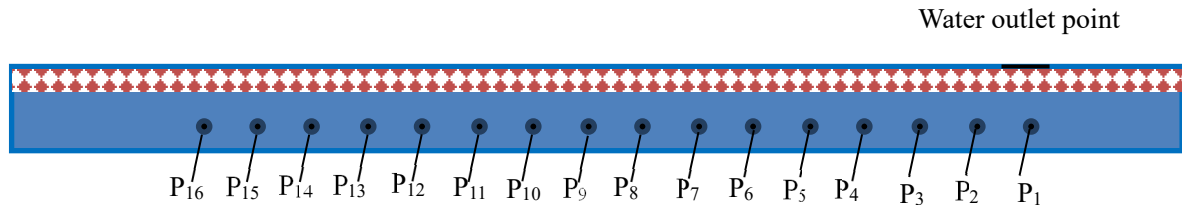


Fig 7. Water finding diagram

Write the BP neural network algorithm using MATLAB, create input and output layers, and import data for deep learning[8]. By comparative analysis, set the number of hidden neurons to 35. The hidden layer uses tansig transfer function, and the output layer uses purelin transfer function to establish a water outlet position prediction model based on BP neural network. Train and predict the network, and select 5 sets of data for prediction through the trained network, and compare it with the actual water outlet position. The neural network structure established[9]. The Levenberg Marquardt algorithm is used for training, which typically requires more memory but less time.

The BP neural network regression analysis diagram is shown in Figure 8, with four images showing the regression analysis diagrams for training samples, validation samples,

test samples, and overall prediction. The R value represents the correlation coefficient, which is obtained by calculating the linear correlation coefficient between the predicted value and the actual value. The R value range is between -1 and 1, where 1 represents complete positive correlation, -1 represents complete negative correlation, and 0 represents no linear relationship. In neural networks, The calculation of R value can help us evaluate the predictive performance of the model. From the graph, it can be seen that the correlation coefficients of the training samples, validation samples, and test samples are 0.99938, 0.9993, 0.99934, and 0.99936, respectively, indicating that the obtained BP neural network model is relatively accurate and can accurately predict the distance between the water outlet point position and the detection instrument position.

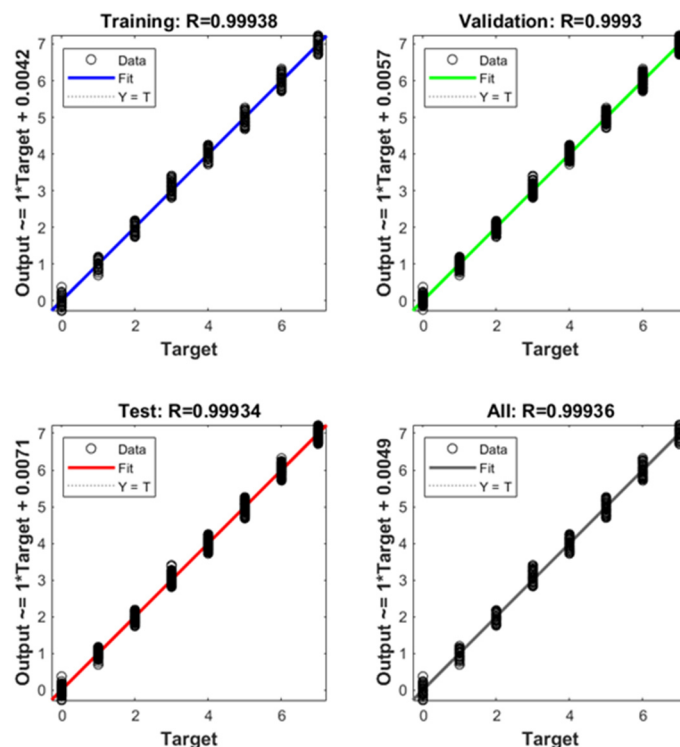


Fig 8. Regression analysis chart

4. Summary

This article realizes the method of detecting water content data in a horizontal well and successfully predicting the position of the water outlet through a BP neural network model. This method has certain practical significance and provides a new and reliable method for water exploration technology.

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