

Reservoir Development Geologic Modeling and Residual Oil Prediction Research

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Abstract. The aim of this thesis is to investigate the geological modeling methods in reservoir development as well as residual oil prediction techniques. Geological modeling is a crucial step in oilfield development, which involves the three-dimensional description of subsurface reservoirs and helps to better understand reservoir properties. Residual oil prediction, on the other hand, is an estimation of the future production capacity of the reservoir and is crucial for decision making and resource management. This study explores different geological modeling methods, including seismic inversion, core analysis, and wellbore data, and introduces a variety of residual oil prediction techniques, including numerical simulation and statistical methods. Through example analyses and case studies, this paper demonstrates the application of these methods in practical reservoir development and their potential to improve reservoir development efficiency and residual oil prediction accuracy.

Keywords: Reservoir characterization; geological modeling; static classification evaluation; reservoir inhomogeneity

1. Introduction

Reservoir development is one of the core aspects of the petroleum industry and involves the extraction of oil and gas resources from underground reservoirs. Geological modeling and residual oil prediction are two crucial aspects in the reservoir development process. Geological modeling aims to create an accurate three-dimensional representation of the subsurface reservoir to help engineers and geologists better understand the nature and structure of the reservoir[1]. Residual oil prediction, on the other hand, is an estimation of the future production capacity of a reservoir, which helps in decision making, resource management and production optimization. This study will explore different geological modeling approaches and residual oil prediction techniques to improve the efficiency and sustainability of reservoir development[2-4].

1.1 Geological modeling methodology

1.1.1 Seismic inversion

Seismic inversion is a commonly used geological modeling method to infer the nature of a reservoir by analyzing the way seismic waves propagate through the subsurface reservoir. This method provides a high-resolution image of the subsurface structure and helps to

determine important parameters such as the layers, thickness and porosity of the reservoir[5].

1.1.2 Core analysis

Core analysis is a method of obtaining reservoir properties by laboratory testing of reservoir rock samples[6]. This method provides detailed information about the porosity, permeability, pore structure and fluid properties of the rock. Core analysis is often combined with seismic inversion data to create more accurate geologic models.

1.1.3 Wellbore data

Wellbore data, including wellbore logging and wellbore sampling, are key tools for monitoring wellbore conditions in real time. These data provide information on reservoir properties, the location of the oil-water interface and reservoir pressure[7]. Used in conjunction with seismic inversion and core analysis, wellbore data can help construct more comprehensive geologic models[8].

1.2 Current status of domestic and international research

China's low permeability oil fields are widely distributed, and the four major basins such as Jungar, Songliao and Bohai Bay are rich in low permeability oil reservoirs, which are very rich in resources [9]. As of 2018, according to the statistics of relevant departments, low

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permeability oil reserves occupy nearly half of PetroChina's proven oil geological cumulative reserves, up to more than 40%, so how to efficiently and economically develop low permeability oil reservoirs has gradually become a worldwide problem[10-12].

1.2.1 Sedimentary feature spreading study

Many scholars in China have also carried out fine studies on deltaic outcrops and modern sedimentation. Li Sitian and other geologists have completed a fine comparative study of the Jurassic Yan'an Formation deltaic outcrops in the Ordos Basin, and at the same time, they have also compared the estuarine dams, mat sands and other sands, which not only established the stratigraphic framework of the basin, but also delineated the internal genesis phases of the sedimentary system. Wang Defa and other geologists carried out research on two deltaic deposits in Daihai Lake, Inner Mongolia, and carried out a comprehensive study based on the theory of "fluvial-phase configuration", and arrived at the technical scheme of dividing the interface of land-phase deltas into 6 levels, and summarized the basic reasons for the composition of the 10 types of land-phase deltaic deposits. Liu Ziliang and other geologists assembled the sedimentary microphase of thick sand body in front of the delta in Longdong area of Ordos Basin, compared the lateral tracking profiles, explored the identification signs of the interface of sedimentary sand body in front of the delta, and classified 9 kinds of constitutive elements[13].

1.2.2 Reservoir fine characterization studies

"Fine reservoir description" technology is based on the theories of sedimentology, tectonic geology, petroleum geology, etc., using computer as a means, comprehensively applying seismic stratigraphy, logging geology, reservoir geology, geostatistics, etc. to qualitatively and quantitatively describe the type of oil and gas reservoirs in three-dimensional space, the external geometric shape, size, reservoir parameters changes and fluid distribution. internal structure, reservoir parameter changes and fluid distribution. The technology of "fine reservoir description" maximally applies computer visualization technology to show the change rule of the reservoir in three-dimensional space, so as to carry out detailed and accurate description of the reservoir, as well as comprehensive and comprehensive evaluation. At the same time, this technology is also an oil field into the development, with the deepening of the degree of exploitation and dynamic data increase, the fine geological characteristics and potential research, as well as constantly improve the process of reservoir geological model[14]. Fine reservoir description is equivalent to the adjustment stage of reservoir management, which is the process of entering the middle and late stages of oilfield development, making full use of modern science and technology and theories, especially computer technology, geology, sedimentology, reservoir geology and other theories on the basis of a large amount of historical data, and serving for the excavation of the maximum potential

of the reservoir. Reservoir fine description is a multidisciplinary and comprehensive research on reservoirs, which takes the difficult development unit as the research object, establishes a fine three-dimensional geological model as the basis, reveals the spatial distribution law of residual oil as the focus, and determines the measures for digging out the potential and improving the recovery rate as the ultimate goal, and it is a systematic project integrating multiple disciplines such as geology, logging, numerical simulation, and reservoir engineering, and so on[155].

2. Residual oil prediction techniques

2.1 Numerical simulation

Numerical simulation is a residual oil prediction method based on a mathematical model that predicts future production capacity by simulating fluid flow and rock deformation during reservoir recovery[16]. This method can take into account complex geologic conditions and recovery strategies and provides detailed information on reservoir dynamics. The first step in numerical simulation is to develop a mathematical model that represents the reservoir. This model takes into account the reservoir's geological characteristics, fluid properties, permeability, porosity, and other parameters. Typically, the reservoir is partitioned into a three-dimensional grid and each grid cell contains information about the region. Numerical simulations use the equations of conservation of constant mass, conservation of momentum, and conservation of energy to model the flow of fluids through the reservoir[17]. These equations take into account parameters such as pressure, temperature, and saturation of the fluid, as well as the physical properties of the rocks in the reservoir. In addition to the fluid flow, the numerical simulation also considers the deformation behavior of the rock. This includes factors such as the stress distribution of the rock, fracturing conditions, and porosity variations, all of which affect the release and flow of residual oil[18].

2.2 Modeling and parameterization

In this case, a three-dimensional numerical model has been developed, taking into account geological features, reservoir fluid properties, petrophysical properties and the location of existing extraction wellheads. The model was discretized using the finite element method and computed using conventional simulation software.

2.2.1 Activation function

An activation function is a function that runs on neurons, by which the neural network model is approximated as a nonlinear function, so that the neural network can be applied to numerous nonlinear models. With a linear activation function, the input is passed directly to the output without any correction:

$$f(x) = x$$

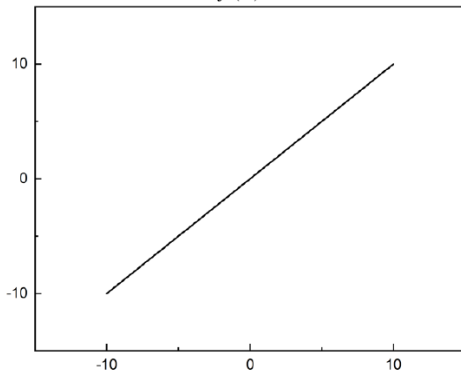


Fig. 1 Schematic diagram of linear activation function

Sigmoid activation function, it will be a sequence of data through the calculation of compression to a large negative to 0 approximation, a very large positive to 1 approximation layer, the value of the output result that corresponds to the predicted probability of the data. Probabilistic prediction model, between 0 and 1, makes it very possible to apply it to the output, the formula is shown below:

$$f(x) = \frac{1}{1 + e^{-x}}$$

The disadvantage of the Sigmoid activation function is that it is prone to the phenomenon of gradient vanishing, and the training process converges slowly due to the large training index.

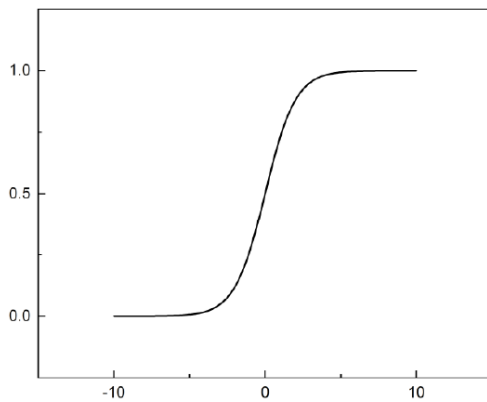


Fig. 2 Schematic diagram of Sigmoid activation function

2.3 Simulation results and residual oil prediction

Through numerical simulation, we modeled the dynamic behavior of the reservoir, including oil production rate, water drive curve, bottomhole pressure and other parameters. Based on the simulation results, we estimated the oil reserves in the remaining reservoir and predicted the future production capacity. The model evaluation indexes are as follows, and the correlation coefficient is used to assess the degree of correlation between the predicted and real values of the model:

$$\frac{\sum(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})}{\sqrt{\sum(y_i - \bar{y})^2} \sqrt{\sum(\hat{y}_i - \bar{\hat{y}})^2}}$$

Where n is the number of training variables and the root mean square error of the prediction set RMSEP response model performance on test data:

$$RMSEP = \sqrt{\frac{1}{m} (\hat{y}_i - y_i)^2}$$

2.4 Analysis of results and decision-making

By analyzing the simulation results, we can optimize the reservoir's recovery plan, including adjusting wellhead production, water injection strategy, and wellhead location. These decisions will help to increase the production capacity of the field and extend the life of the reservoir.

3. Composite function RNN-based oil quantity prediction algorithm for oil wells

3.1 Problem analysis

Oil well production forecasting is a time-series forecasting task, where data from various influencing factors are used to forecast oil production from oil wells of future data for prediction. Among them, RNN has good effect in solving this kind of problems, which is more accurate than traditional statistical learning methods. RNN can better solve the above problems, not only can it take into account the influence of related geologic development factors on the oil production of wells, but also can take into account the correlation of the oil production of wells in the time dimension, which has strong prediction accuracy and strong adaptability to the environment.

3.2 Algorithm Design Principles

The data of the input model in the experiment is represented by a multidimensional matrix, while realized by dot product between the matrix and the matrices. In order to evaluate the accuracy of the oil production prediction model for oil wells, the main purpose is to measure the error between the predicted value and the true value. The smaller the error, the closer the predicted value is to the true value. Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) are selected as the evaluation indexes, and the calculation formula is as follows[19].

$$RMSE = \sqrt{\frac{1}{n} (y_i - \hat{y}_i)^2}$$

$$MAE = \frac{1}{n} |y_i - \hat{y}_i|$$

$$MAPE = \frac{100\% |y_i - \hat{y}_i|}{y_i}$$

3.3 Experimental Flow

- (1) Processing of oil production data from oil wells, as well as the division of the data set is processed and sliced according to the process in 2.2.
- (2) The inputs of both proposed models are pump diameter, pump efficiency, formation thickness, and well oil production.
- (3) The training set is trained separately for all models and experiments are conducted using the optimal function of the loss function for all models using the selection of the cost function. And the hyperparameters designed in this paper are continuously optimized empirically so as to perform grid search to get the best experimental results[20].
- (4) Save each model and test the unified data, while using the evaluation index in 3.2 to compare and analyze the experimental results, any model in any well are repeated 20 times, in order to ensure the accuracy of the test results, the average value is taken as the final evaluation index results.

3.4 Experimental results of well oil production prediction

Oil well production data is data that shows correlation with time, and its overall trend will show fluctuation with time. Therefore, the multiplicative decomposition model is used. The four data of T1 and T2 wells in T block and H1 and H2 wells in H block are used as experimental data to analyze the basic characteristics of oil production data and the characteristics of each component after STL decomposition. After continuous debugging, it is found that the STL decomposition is most effective at 15, which can ensure that the oil production data of the wells are fully utilized.

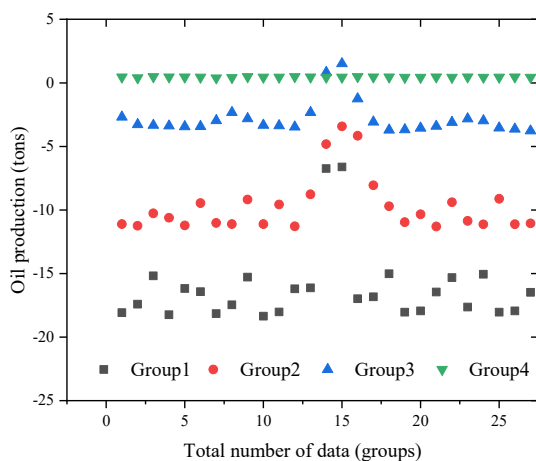


Fig. 3 Schematic diagram of STL decomposition of well T1 in T-break block

Overall, the STL decomposition results in a smoother trend graph, with a more pronounced general trend at a given stage. Relative to the original data, there is much less fine noise and it is changed to a smoother curve. It also has a suppression effect on the singular values at a certain moment. As for the period term, two of the cycles are selected as examples, and it can be seen that the pattern of each cycle is obvious and smooth. Therefore,

the trend and cycle terms after STL decomposition reflect the trend and cycle pattern of daily oil production of the four wells more accurately and comprehensively.

4. Conclusion

Geological modeling and residual oil prediction are indispensable aspects of the reservoir development process. This paper discusses different geologic modeling approaches and residual oil prediction techniques, and demonstrates their use in real-world oilfield development through case studies. By building complex mathematical models that take into account geological features and fluid behavior, numerical simulation can provide reliable residual oil estimates and support decision making. The case study in this paper demonstrates the application of numerical simulation in conventional reservoirs, providing a powerful tool and methodology for reservoir development. The STL of time series decomposition is used to decompose the raw well oil production data so that the effect of noise such as residuals can be removed and smoother trend and period terms with stronger correlation can be obtained.

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