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The Study of Optimizing Reservoir Model Using Experimental Design in Stochastic Models

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Abstract: In response to the main problems in commonly used model selection methods, a method was proposed to apply the concept of experimental design to the optimization of uncertain reservoir models. Firstly, based on the actual situation of the oil field, the uncertain variables were determined that affect the geological reserves of the model and their possible range of variation, and experimental design was used to determine the modeling plan. Then, multiple geological models were established and reserves were calculated, and multiple regression was performed between uncertain variables and the corresponding geological reserves of the model. Finally, Monte Carlo simulation technology was applied to determine the parameters of the P10, P50, and P90 models for probabilistic reserves, and P10, P50, and P90 models were established. This method is not only more objective and time-saving in the application process, but also can determine the main geological variables that affect geological reserves, providing a new idea for evaluating the uncertainty of geological reserves.

Key words: Uncertainty evaluation, experimental design, random modeling, model optimization.

1. Introduction

Since the 1980s, with the wide application of geostatistics, reservoir stochastic modeling technology has been developed rapidly in the exploration, development and production of oil and gas fields [1]. Random modeling not only provides multiple models with equal probability implementation, but also the introduction of variation functions enables the model to more reasonably reflect the spatial heterogeneity of the reservoir. Due to the fact that random modeling can provide multiple model implementations, it is crucial to select one or several models for numerical simulation research in practical applications. Therefore, the optimization of model implementations is crucial [2, 3].

Common random model screening methods include geological pattern screening method, multi-parameter nesting method, arithmetic mean method, numerical simulation method and probabilistic reserves method (Table 1). These model optimization methods have been widely applied in reservoir stochastic modeling, but there are also some problems, such as time-consuming and laborious specific operations; Subjective factors have a significant impact. The uncertainty range of geological variables cannot be fully considered [4-7].

Based on the analysis of the above model optimization methods and actual production needs, this paper proposes a method for optimizing geological models through experimental design through the practice of multiple oil fields. In practical applications, firstly, geological variables and their variation ranges are determined based on the actual situation of the oil field and research purposes. The variation range of each variable is described by the maximum, minimum, and average values, and the modeling scheme is determined through experimental design. Based on this, a corresponding model was established and its reserves were calculated. Multiple regression was performed on the geological reserves

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Table 1 Comparison of conventional stochastic model optimization methodology.

Method	Description	Advantages	Disadvantages
Geological pattern screening method	Compare the implementation of each model with the geological pattern, and select the model that matches the geological pattern to a greater extent	The model implementation can better match the geological conceptual schema	It takes a lot of time and is greatly influenced by subjective factors
Multi-parameter nesting method	A nested screening method for comprehensive geological models, statistical parameters, reservoir heterogeneity, and dilution testing	The factors considered in this method are relatively comprehensive, and the selected model not only conforms to geological laws but also meets the statistical characteristics of the data	During the specific operation process, a lot of time is required to compare and verify
Arithmetic mean method	Carry out arithmetic mean for multiple model implementations, and the average model obtained is taken as the final preferred model	Easy to operate	The final model is smoother, which not only changes the heterogeneity of the reservoir, but also changes the statistical distribution characteristics of the model
Numerical simulation method	Output the model into reservoir simulation and optimize the model through dynamic methods such as streamline simulation history fitting	The participation of reservoir engineers is required, and the selected model can be directly used for reservoir simulation	The number of model implementations is large, and it is not realistic to filter each model through numerical simulation
Probabilistic reserve method	Calculate the geological reserves implemented by all models, create a probability distribution map of geological reserves, and select the models corresponding to P10, P50, and P90 reserves from it	Quick and specific operation	Due to the fact that multiple model implementations are based on a set of input parameters, the model results cannot fully consider the uncertainty range of geological variables

of each variable and corresponding model to obtain a multiple regression equation. Then, Monte Carlo simulation technology is applied to determine the probability distribution of reserves, while determining the simulation parameters of the P10, P50, and P90 models. Finally, P10, P50, and P90 models were established and coarsen as needed to provide input data for reservoir simulation.

2. Reservoir Characteristics

The D oilfield is located in the Bohai Basin. The main target layer of D oilfield is the Kavonella Formation, which is further subdivided into eight sections C1-C8. Sections C1, C3, C5, and C7 are mainly composed of fan delta sand bodies, with high porosity and permeability. The porosity is generally 20% -31%, and the permeability is generally $(0.987\text{-}2.961)\times10^{-3}$ μm^2. The C2, C4, C6, and C8 sections are composed of delta shelf mud. The main oil bearing series of the oilfield is the C5 section, with C5a and C5b being the main oil bearing sand bodies. The formation of oil and gas reservoirs is mainly controlled by factors such as oil and gas injection abundance, fault sealing conditions, structural location, trap size, and reservoir properties. The research area data include drilling and logging data from 28 wells, as well as reservoir top structure maps and seismic data volumes interpreted based on three-dimensional seismic data.

3. Uncertainty Analysis

Based on the actual exploration and development of oil fields, the following six geological variables are selected to evaluate the uncertainty of the model: the variation function of sedimentary micro (channel and sheet sand), the volume percentage of channel, and the volume percentage of sheet sand, the porosity variation function, the lower limit of porosity, and the oil-water interface. This mainly discussed the determination of the range of values for three variables.

3.1 Sedimentary Micro Variation Function Parameters

The differential function of deposition micro-facies transformation is an important parameter that determines the geometric size of micro-facies space. The statistical results of outcrops, modern sedimentary surveys, and flume experiments show that the spatial geometric parameters of micro-facies in similar sedimentary environments, such as aspect ratio and aspect thickness ratio, vary within a certain range [8]. For a specific oil field, although it is not possible to accurately estimate the parameters of its lateral variation function due to limited data, the vertical parameters can be accurately estimated based on logging data. Then, based on the aspect ratio and aspect thickness ratio of the analogy, the lateral variation function was further determined. Delta is developed in steep slope areas of depressions, with fast water flow speed. Therefore, the river channel is shallow, and the width to thickness ratio of sand bodies is relatively large. In the modeling process, the river channel, sheeted sand, and dam body are selected as simulation targets. Vertical parameters are calculated using well data, and their lateral parameters are selected based on analog data. The azimuth of the variation function is determined based on the direction of the antique source. The specific parameter selection is shown in Table 2.

3.2 Volume Percentage of Channel and Sheet Sand

Due to significant differences in the distribution of reservoir parameters such as porosity and permeability among different sedimentary micro-facies, the volume percentage of each sedimentary micro-facies is crucial for attribute modeling in geological models and has a significant impact on the reserves of the model. The interpretation results of single well sedimentary micro scale from 28 wells in the study area were statistically analyzed, and the volume percentages (max, min, and Avg) of each sedimentary micro scale were obtained as shown in Table 3.

3.3 Lower Limit of Porosity

The lower limit value of effective reservoir thickness is not only used to determine the thickness of the reservoir at the well point, but also directly used to determine the effective volume of rocks in three-dimensional geological models. In geological modeling, the lower limit of porosity is usually used to determine the effective volume of the model. Therefore, the lower limit of porosity has a direct impact on the geological reserves and water volume of the geological model. The lower limit of porosity for the effective thickness of reservoirs in D oilfield is 11%, and there are not many test data points between 10% and 12%. The selected lower limit of porosity has some uncertainty. Taking into account the potential risks and potential caused by the lower limit of porosity, 11% was chosen as the mean, 10% as the minimum value, and 12% as the maximum value.

3.4 Oil Water Interface

The changes in the oil-water interface have a significant impact on the reserve calculation results. The oil-water interface of the northern fault block in the D oilfield has not yet been explored, and the current value is -4,520 ft from the bottom boundary of the oil layer interpreted by logging, with an average thickness of about 30 feet. When considering the uncertainty of the oil-water interface, the current bottom depth of the oil layer was selected as the minimum value, half of the oil layer thickness was pushed down by 15 ft, which is

Table 2 Parameters of variogram function for sedimentary micro-facies.

Micro-facies	Variation function parameters /m						
	Main range			Secondary range			vertical range azimuth angle/°
	Min	Avg	Max	Min	Avg	Max	
River course	300	500	900	150	300	500	110
Sheeted sand	800	1,000	1,200	700	900	1,000	20

Table 3 The volume percentages of each sedimentary micro scale.

Sedimentary micro	Max	Min	Avg
river course	0.49	0.39	0.44
Sheeted sand	0.53	0.43	0.48

-4,505 ft as the average value, and then pushed down by 15 ft, which is -4,535 ft as the maximum value.

4. Experimental Design and Establishment of Experimental Models

4.1 Selection of Experimental Design and Modeling Scheme

A designed experiment is an experiment or a series of experiments that observe changes in experimental results by purposefully changing input variable values, in order to determine the reasons for the changes in results. Experimental design is mainly applied in the fields of engineering, physics, and chemistry. The earliest application in the petroleum industry can be traced back to the 1960s, but at that time it was mainly applied in physical experiments and still belongs to the field of physics applications. Oil and gas reservoirs are located underground, with limited direct data. Indirect data are limited by various conditions, resulting in uncertainty in describing the spatial distribution and internal attribute parameters of reservoirs, which in turn leads to uncertainty in geological reserves and recoverable reserves. Therefore, theoretically, the process of reservoir description is comparable to physical and chemical experiments, and the concept of experimental design can be applied to reservoir description.

In order to evaluate the impact of a certain variable on the model reserves, multiple simulations should be conducted by changing the value of the variable while ensuring that other variables remain unchanged, in order to determine the impact of the variable on the model results. If the changes in variables are described by maximum and minimum values, then considering the impact of six variables on model reserves, at least 2^6 (64) models are required to comprehensively quantitatively evaluate these variables. If the changes in variables are described by maximum, most likely, and minimum values, then 3^6 (729) models need to be established, which is obviously not achievable in practical applications. The Plackett Burman experimental design can design the optimal modeling scheme. It is designed through screening experiments, mainly targeting situations with a large number of input variables. By screening input variables that have a significant impact on the output results, it avoids wasting experimental resources in later optimization experiments due to too many input variables or some input variables being not significant. Therefore, in the research of D oilfield, the maximum value, the average value, and minimum value are selected to describe the range of variable values. Through Plackett Burman experimental design optimization, only 9 models are needed to reasonably evaluate the uncertainty of reserves. The modeling scheme provided by the experimental design is listed in Table 4.

Table 4 Plackett-Burman experimental design.

Model	Sedimentary micro-facies change difference function	River channel percentage	Sheet sand percentage	Porosity variation function	Lower limit of porosity	Oil water interface (altitude)/m
Model 1	Max	0.39	0.43	Min	0.10	-4,535
Model 2	Max	0.49	0.43	Min	0.12	-4,505
Model 3	Max	0.49	0.53	Min	0.10	-4,535
Model 4	Min	0.49	0.53	Max	0.10	-4,505
Model 5	Max	0.39	0.53	Max	0.12	-4,505
Model 6	Min	0.49	0.43	Max	0.12	-4,535
Model 7	Min	0.39	0.53	Min	0.12	-4,535
Model 8	Min	0.39	0.43	Min	0.11	-4,505
Model 9	Avg	0.44	0.48	Avg	0.11	-4,520

Based on the modeling scheme designed in the above experiment, under the constraints of constructing a framework model, models of sedimentary facies, lithofacies type, porosity, permeability, saturation, and net to gross ratio are established in sequence.

4.2 Sedimentary Micro-facies Model

The sedimentary facies of the target layer are delta facies, and the main sedimentary micro-facies are distributary channels, estuarine bars, and front edge sheet sand. The sediment source during the sedimentation period comes from the northeast direction of the oil field. Guided by the regional sedimentary background, combined with data from a single well, sedimentary micro-facies interpretation is performed, and then the interpretation results of the single well sedimentary micro-facies are discretized into micro-facies codes. The estimated variation function and volume percentage of each micro-facies are used as conditional data, and the sedimentary sub facies diagram is used as a constraint trend. Based on the experimental design of the modeling scheme, 9 sedimentary micro-facies models were established using the Sequential Indication Simulation algorithm.

4.3 Attribute Model

Based on the results of core analysis, the lithology classification criteria are determined (porosity greater than 10% refers to medium coarse sandstone, 8%-10% refers to silt-fine sandstone, and less than 8% refers to mudstone). At the same time, referring to lithology logging data, the porosity curve calibrated by the core is used to classify the lithology at the well point, and discrete lithology data are formed. In the process of 3D geological modeling, the discretization lithology curve is used as the basic input data, the sedimentary micro-facies model is used as the constraint, and the volume percentage of lithology is used as the conditional data. The method of establishing the model still adopts sequential indication simulation, and during the modeling process, it is necessary to ensure that the volume percentage of each lithology in the model is basically consistent with the target value.

The resolution of seismic data in D oilfield is very low, so the establishment of porosity models cannot be constrained by seismic data. Under the control of the lithofacies model, the porosity model is established using the logging interpretation porosity calibrated by the core as the basic input data, and the statistical distribution characteristics and variation function of the logging porosity are used as conditions. The sequential Gaussian simulation algorithm suitable for continuous variables is used to establish the porosity model.

Under the constraints of the rock type model, the well logging interpretation permeability calibrated by the core is used as hard data, and the statistical distribution characteristics of well point permeability in each geological layer and the variation function model are used as limiting conditions. The porosity model is used as soft data, and a three-dimensional permeability model is established using the sequential Gaussian collaborative simulation method. For the saturation model, the relationship between water saturation and porosity, permeability, and oil column height is obtained based on the capillary pressure curve statistics as follows:

$$S_w = \mathrm{e}^{5.531\left(0.907-0.0012\mathrm{h}-0.01\sqrt{K/\Phi}\right)}$$

In the formula: S_W is the water saturation, %; h is the height of the oil column, m; K is the permeability, 10^{-3} μm^2; Φ is the porosity, %.

Using the above formula, a saturation body can be obtained through porosity model, permeability model and oil column height calculation. The data body is soft data, and the saturation interpreted by logging is hard data. The saturation model can be obtained through sequential Gaussian collaborative simulation.

5. Models

5.1 Multiple Regression Formulas for Uncertain Variables and Model Geological Reserves

The geological reserves of 9 models were calculated based on the previously established reservoir attribute model and other reserve parameters. The maximum geological reserve is 64×10^4 m^3, minimum 41×10^4 m^3. Multiple regression was performed on the geological variables of the model and the corresponding geological reserves of each model, and the following regression formula was obtained:

$$OOIP = 89 - 0.87\gamma_S - 9.68f_S + 50.1f_m - 0.32\gamma_p - 525.26\varphi_{cut} + 4.23OWC$$

In the formula: *OOIP* is the geological reserve, 10^4 m^3; r_s is the variation function of the river channel; f_s is the percentage of the river channel, decimal; f_m is the percentage of sheet sand, decimal; r_p is the simulated variation function of porosity; φ_{cut} is the lower limit of porosity, decimal; *OWC* is the oil-water interface.

The reserves of the 9 models are very close to those calculated by the regression formula, with errors of less than 1%. The regression formula well reflects the relationship between uncertain variables and geological reserves.

5.2 Probabilistic Reserve Simulation

In the process of evaluating the uncertainty of geological variables, Monte Carlo technology is widely used, and the evaluation of geological reserve uncertainty is one of its important applications. According to the aforementioned multiple regression formula, Monte Carlo technology is applied to evaluate the uncertainty of geological reserves, and parameters of P10, P50 and P90 models are selected to obtain the final uncertainty model. The value range of geological variables is shown in Table 5.

A total of 50,000 geological reserve simulations were conducted using Monte Carlo simulation to obtain the cumulative probability distribution of geological reserves. Simultaneously obtained, the conservative geological reserve P90 is 46×10^4 m^3, with the most likely geological reserve P50 of 50.9×10^4 m^3, optimistic geological reserve P10 is 54.7×10^4 m^3. The difference between the reserves of the P10 and P50 models and the reserves simulated by Monte Carlo is only 3%, while the difference between the reserves of the P90 model is about 10%, so the regression formula obtained through experimental design has a certain predictive ability.

The Monte Carlo simulation method can provide an evaluation of the impact of each variable on geological reserves. The change in the lower limit of porosity has the greatest impact on the geological reserves of the model. Due to the low porosity and low permeability reservoirs in the D oilfield, there are many points with porosity ranging from 10% to 12%, so the lower limit of porosity has a significant impact on the reserves of the model. The second influencing factor is the oil-water interface, and changes in the oil-water interface will affect the oil bearing area. The larger the value, the greater the geological reserves. The third influencing factor is the percentage content of the rock type. The remaining three variables (variation function of sedimentary micro-facies simulation, percentage content of sedimentary micro-facies, and variation function of porosity simulation) have little impact on reserves.

Table 5 Range of geological variable values.

Geological variables	P10	P50	P90
Channel variation function	Min	Min	Max
River percentage	0.392	0.442	0.492
Percentage of sheet sand	0.431	0.481	0.531
Porosity variation function	Min	Min	Max
Lower limit of porosity	0.10	0.11	0.12
Oil water interface (altitude)	-4,505	-4,520	-4,535

6. Conclusion

(1) Compared to the commonly used model selection methods, the screening model method using experimental design concepts has the following advantages. Firstly, it is relatively objective. As long as the reservoir modeling is carried out according to this method, P10, P50, and P90 models can be reasonably selected, thereby avoiding model selection bias caused by subjective randomness; Secondly, it saves time and improves work efficiency. Compared to geological mode screening, nested screening, and reservoir simulation validation methods, this method is more efficient; In addition, this method also fully considers the uncertainty of geological variables. As different modeling schemes consider the possible range of changes in each geological variable, the established series of models more reasonably reflect the underground geological characteristics.

(2) The combination of multiple uncertain geological variables and model geological reserves with multiple regression methods and Monte Carlo simulation technology can further evaluate the sensitivity of geological variables to the impact of geological model reserves, thereby determining the main uncertain variables that affect the model results and providing a basis for the next evaluation of oil and gas fields.

(3) The experimental design provides a new approach for evaluating the uncertainty of geological reserves. This method can not only determine the main geological variables that affect geological reserves at the current stage, but also evaluate the uncertainty of geological models, provide a more reasonable static model for reservoir simulation, and ultimately provide reasonable technical support for project decision-making.

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