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RESEARCH PAPER

Improving the accuracy of geological model by using seismic forward and inverse techniques

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Abstract: Sequential Gaussian simulation method is taken as an example to analyze the characteristics and defects of stochastic simulation methods, and a modeling strategy is proposed that is based on the results of seismic inversion to improve modeling accuracy. Stochastic simulation can only achieve "mathematical reality" by recovery of parameter's macro statistical regularity through examples, and seismic forward model can verify whether the simulation results deviate from the "geological reality". Seismic forward modeling can verify the reliability of the geological model, and the results of geological modeling constrained by seismic inversion can improve the accuracy of the model to achieve the "geological reality". For braided river delta, a modeling strategy constrained by seismic inversion results in the condition of "multi-levels" and "multi-conditions" is put forward. For lithofacies modeling, division of lithofacies in single well acts as the first variable; in the stage of exploration and development, lithology probability and lithology body act as the second variable respectively, and then establish facies models. For property modeling, take lithofacies model and the seismic impedance as the first variable and the second variable respectively to create property model, in the condition of horizontal and vertical impedance constraints. The proposed modeling strategy maintains the statistical regularities of input data, keep a better consistency with seismic data, and match with dynamic field production.

Key words: stochastic simulation; variogram; seismic forward; seismic inversion; facies-controlled modeling; seismic constraint; constraint modeling

Introduction

Reservoir geological modeling is aimed at three-dimensional quantitative description of the distribution of various reservoir parameters (facies, porosity, permeability, saturation, etc.) to guide exploration and development of oilfields. As a space simulation and prediction tool, geostatistics has been widely applied in reservoir modeling and other fields since the 1960s [1–8]. In China with most of the oilfield entering the middle and late development stage, the main target of geological modeling is studying remaining oil distribution. In recent years, conventional static or conceptual models can hardly meet the demands of oilfield production, so stochastic simulation has been frequently used to build reservoir geological model [4–8]. Currently, there are a number of stochastic simulation methods [9–11], but all these methods should be applied according to their own applicable conditions, and there does not exist a reservoir modeling method suitable for all depositional environments. Thus, worldwide scholars continue to improve the algorithm to adapt to the complex geological conditions and describe the underground reservoir characteristics as realistic as possible [11–14].

Stochastic simulation can produce multiple realization of equal probability. From the mathematical point of view, the probability of multiple simulations is equal, and follows the law of prior probability characteristics, so each model is reasonable. But from the oilfield production point of view, by the application of these simulation and practice to simulate reservoir values, all the models cannot fit correctly once. Generally, each model need to be regulated manually more than 10 times [15–16], and multiple models can achieve the same matching result [14–17], therefore these models are not accurate. Thus, these realizations conform to the mathematical properties of reservoir, to some degree, and just approach the "mathematical reality" rather than "geological reality".

In this paper, taking the widely used sequential Gaussian simulation method as an example, mathematical reality properties of stochastic simulation are analyzed, seismic forward modeling is employed to analyze the differences between the result of stochastic simulation and the "geological reality". And the modeling strategy constrained by seismic inversion results in the condition of "multi-level, multi-condition" is

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proposed. So the simulation results continue to approach the "mathematical reality" and improve crosswell prediction accuracy to approach "geological reality" in order to guide further deployment of oilfield development program effectively.

1 Mathematical properties of stochastic simulation

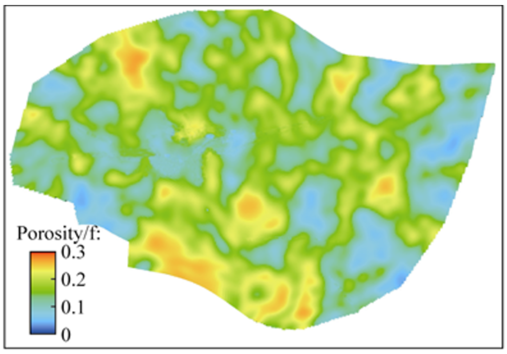
Based on statistics of geologic body parameters, stochastic simulation technique is a geomathematical method which takes variable probabilistic and structural properties in space into consideration. Sequential Gaussian simulation algorithm has two main types of input parameters: probability distribution function and variogram. The probability distribution function is used to describe the data distribution pattern, and the variogram is used to describe the structural feature in space of geological body through triple directional range (main variable range, secondary variable range, vertical variable range) to control the geological formation.

Taking offshore oil field A in the study region as an example, isotropic variogram function (the main variable range and the secondary variable range are the same) and anisotropic variogram function (the main variable range and the secondary variable range are different) were adopted to simulate the porosity of reservoir respectively. The results of simulation behave a near round and near ellipse shape of high porosity values area (Fig. 1). The analysis of the obtained porosity model shows that output variogram function and data distribution pattern are consistent with the distribution pattern of the input parameters, indicating that the simulation results can reappear the statistical characteristics of input parameters accurately, i.e. the "mathematical reality" characteristics of the stochastic simulation. The distribution pattern of the parameters gained by sequential Gaussian simulation method may be irregular in dense well pattern, but they match well with the actual sand body. In the area with no wells or few wells, the distribution pattern tend to be specific, as shown in Fig. 1, the near round and near ellipse shape which can not reflect the complexity of actual sand body shape. In the numerical simulation phase of reservoir, a model usually needs to be regulated several times to match with the production-performance data [15–16], although the simulation results coincide with the data macro-statistical pattern, but fail to reflect the realistic spatial distribution of the reservoir parameters, this also goes for other stochastic simulation methods [10–14].

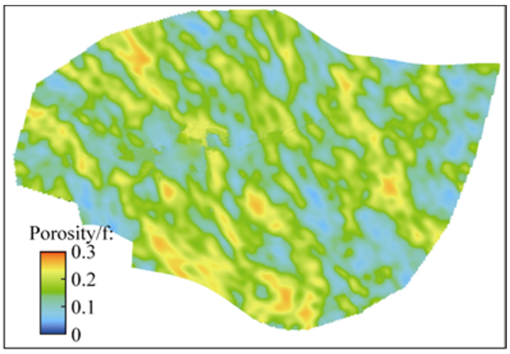
2 Reliability verification of the model with seismic forward

Seismic forward modeling refers to the construction of a known model, and obtaining the geological seismic waveform under specific geological conditions according to some theories. On the contrary, seismic inversion refers to using the receieved seismic wave to speculate the model information. The solution of geophysical inversion is based on the research of forward issues, such as seismic inversion, it builds seismic forward model to examine the inversion computing methods and keep continuous improvement, so the inversion results can approach the geological reality [18–20].

Since the seismic data has such advantages that good lateral continuity and rich spatial information, the reliability of model will be improved effectively by using seismic data as constraint. The difference of wave impedance between strata causes seismic reflection, and wave impedance can effectively characterize the strata attribution, Li Qingzhong presented that wave impedance was the ultimate form of seismic processing, the valid parameter connecting seismic data with lithology, and proposed to describe reservoirs directly [18]. In the case the actual wave impedance underground is known, the seismic waveform data a will be obtained by convolution of wavelets and corresponding reflection coefficients; the seismic waveform data b will be obtained by convolution of wavelets and corresponding reflection coefficient model which is modeled by using stochastic simulation to simulate the wave impedance. The closer the wave impedance model gained by stochastic simulation method and the actual wave impedance, the more consistent seismic data a and b will be. If two wave impedance models are identical, the results of simulation completely reappear the geological reality, seismic data a is entirely consistent with b in theory. Contrarily, the bigger differences between data a and b, the more unreliable the simulation results are.



(a) Isotropy



(b) Anisotropy

Fig. 1 Porosity models obtained using different variogram modeling

Well pattern of oilfield A is irregular, impedance attributes were used to get the fairly reliable variogram [21], and the model of impedance attributes (Fig. 2) was built by using sequential Gaussian simulation method, and the reliability of wave impedance model was verified by using the seismic forward model which was built by Jason software. The seismic section (red) gained from seismic forward modeling and the seismic section (black) from actual measurement were overlapped (Fig. 3), showing there are great differences both in crosswell area and extrapolation area, which indicates that the wave impedance obtained from the stochastic simulation results is quite different from the actual impedance. Thus it implies the stochastic simulation results can not reflect the geological reality accurately.

The impedance volume gained by seismic inversion (Fig. 4) differs from the wave impedance obtained by stochastic simulation (Fig. 2). Impedance volume gained by seismic inversion is faithful to seismic reflection characteristics, and independent on geostatistical parameters. It matches with well data, and be natural transition between wells. Comparison of the seismic section of forwarding modeling of wave impedance data by inversion with the actual seismic section shows the correlation coefficient of them is more than 99% (Fig. 5), which indicates that the seismic inversion result better reflects geological reality than wave impedance from stochastic simulation.

It can be seen that seismic forward modeling can verify the reliability of geological model, and the data of seismic inversion can constrain the modeling effectively. Taking full advantage of the spatial characteristics of inversion data, and using the inversion results (wave impedance, lithological interpretation results) to constrain each phase of modeling (facies modeling property modeling) can improve the accuracy of the model.

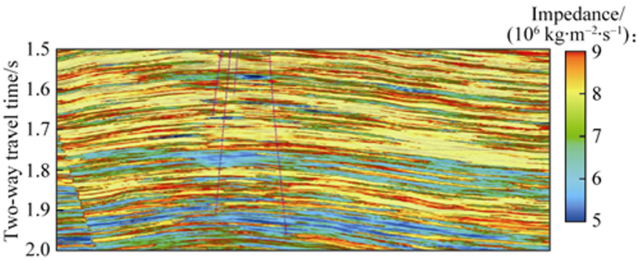


Fig. 2 Impedance attribute section simulated by sequential Gaussian simulation method

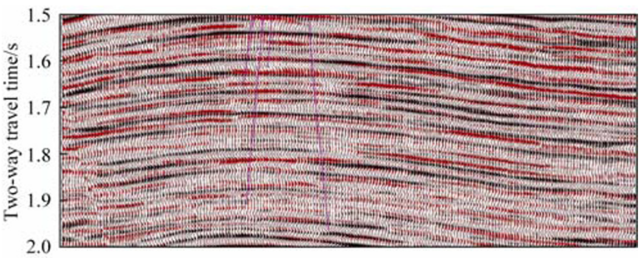


Fig. 3 Comparison between forward model (red) and actual seismic section (black)

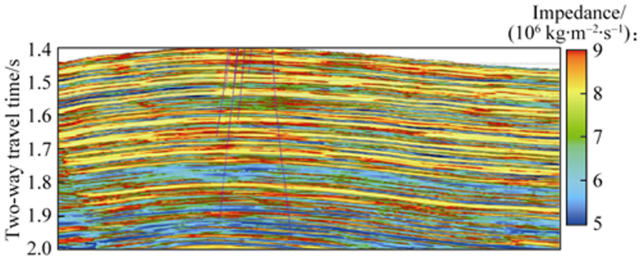


Fig. 4 Impedance attribute section from seismic inversion

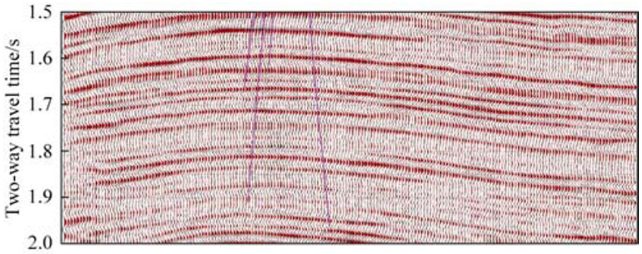


Fig. 5 Comparison between forward model (red) and actual seismic section (black)

3 Examples of modeling constrained by seismic inversion results

Taking oilfield A as an example, this paper discusses modeling strategies of different stages in the modeling constrained by seismic inversion results. In the exploration stage, due to large study area but few wells, the interpretation of results often have multiple solutions, the macro-trend was constrained by the probability in the modeling process, then the sedimentary pattern of the whole area was analyzed; in the development stage, due to smaller study area and more wells, there are higher requirements towards crosswell prediction accuracy, inversion results (lithosome, wave impedance body) are used to constrain the modeling, in order to improve the accuracy of the model.

3.1 Modeling in the exploration stage

The purposes of modeling are different in different stages of oilfield [22]. In the exploration stage, it just needs to figure out the distribution area of favorable zone and macroscopic pattern, so the static conceptual model is enough to meet this purpose which uses the sequential indicator algorithm or multiple point geostatistics method to simulate lithofacies. Generally, in the exploration stage, large study area, sparse wells, and large crosswell interval, result in lower reliability of inversion.

Fig. 6a is the plan of study area, there are 3 exploration wells and 21 production wells. The study area is 200 km^2 within a braided river delta system. Oilfield A is in the delta front belt, where the braided bar distributed between branch channels of near diamond shape is the most favorable reservoir sand bodies. Sequential indicator simulation method based on the variogram can better describe this type of sand bodies morphology. Fig. 6b shows the simulation result. For there are only 3 exploration wells in uneven distribution in the study area, the simulation results can not show the planar dis-

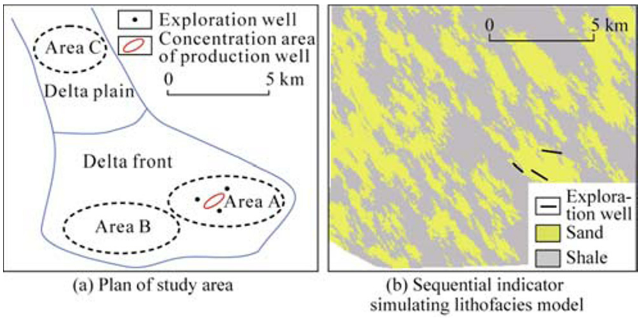


Fig. 6 Lithofacies model built by sequential indicator method

tribution of delta deposits and sand bodies morphology effectively, the simulation results of sand bodies distribution between wells depends heavily on statistical pattern.

In Fig. 6a, area A and area B are located in the same delta front belt, and area C is located in the delta plain belt. Comparison of statistical wavelets extracted from 3 areas shows area A and area B are quite similar in wavelet shape, amplitude spectrum and phase spectrum, but wavelet shape of area C in a different sedimentary facies belt is quite different from the former two (Fig. 7). In different areas, the amplitude, frequency and phase of seismic wavelets are also different, because seismic wavelet is affected by rock composition, structure, porosity and fluid in the wavelet propagation process. In the exploration area where there are few wells, the average wavelet generally can not represent all the wavelets characteristics. Wavelet extraction is the key of seismic inversion, directly affecting the accuracy of inversion results. For large study area, changes in sedimentary facies lead to the deformation of wavelets, so there must be multiple solutions of seismic inversion in the same area.

In consideration of modeling target and seismic inversion uncertainty, therefore, generally, constrained sparse spike inversion which can reflect macroscopic trend is used in exploration stage. In this inversion, wave impedance data is converted into lithological probability body (Fig. 8a) based on the relation between lithology and wave impedance. In addition, modeling of lithofacies should be constrained by co-sequential Gaussian simulation to effectively represent the macroscopic pattern of sand body which belongs to seismic probability body. Fig. 8b is the modeling result constrained by lithological probability body. Compared with Fig. 6b, the simulation result is consistent with the macro-pattern of probability body, so the result is able to reappear the plan form of delta. And the prediction result of crosswell sand body can be explained from the interpretation of sedimentary origin.

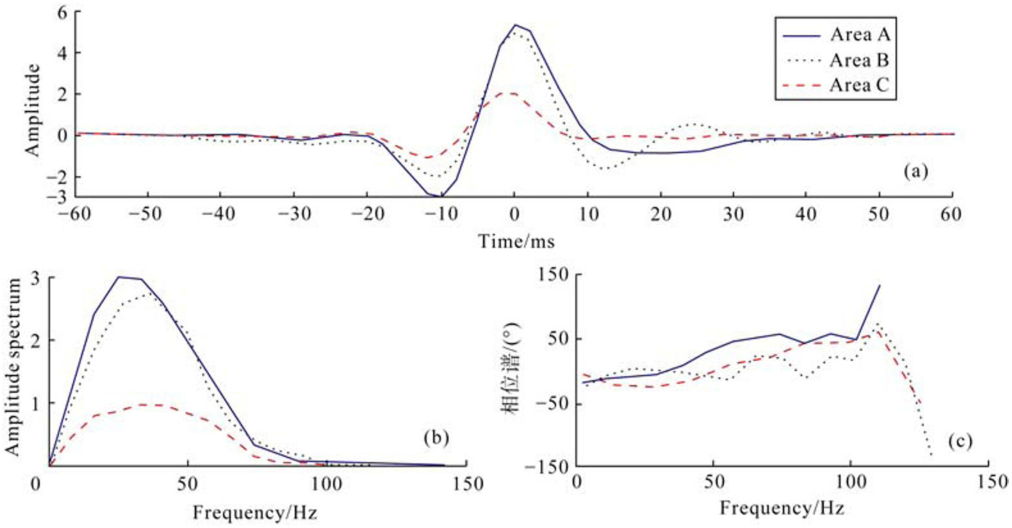


Fig. 7 Comparison of wavelets from different parts of the study area

Some scholars used trend surface or probability surface to constrain the plan [6–7, 23–24], but the plan could only reflect the horizontal distribution of sand body during the deposition time of the strata mentioned above [25], failing to reflect the complexity of vertical evolution in sedimentary environment, especially in the continental sedimentary environment where vertical facies change frequently. But, if probability body is used for constraint, it is equivalent to use multiple probability surface (the number depends on the division degree of the grid) for constraint rather than only one probability surface, which can better reflect the vertical facies change pattern. In addition, during the simulation process of study area, the variogram was gained from plane attribute, which is more accurate gained by well data [21].

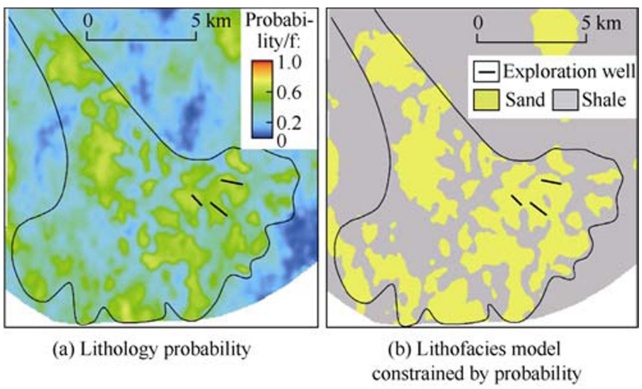


Fig. 8 Lithofacies model constrained by lithologic probability

3.2 Modeling in the development stage

In oilfield development stage, modeling is required detailed reservoir description to define local or crosswell sand body and remaining oil distribution, and further to guide the design of development plan. Generally, this stage requires much higher accuracy of the model with smaller study area and more wells. Oilfield A, an offshore oilfield which has been developed for over 20 years, is currently facing the task of tapping remaining oil to increase production, which sets high requirements on geological modeling. For this reason, lithofacies model and property model of the study area are built under constraint of seismic inversion results.

3.2.1 Lithofacies modeling

The main difference of lithofacies modeling in development stage from exploration stage is lithosome, used to replace probability body to constrain the model. With the increase of modeling requirement and data, the lithofacies modeling constrained by lithosome from inversion directly is more accurate than lithology probability body based on probability distribution, meanwhile the accuracy requirement of seismic inversion and lithology interpretation are higher. In this paper, the uncertainty of lithology interpretation results based on seismic inversion is reduced from the following two aspects.

(1) During inversion process, MCMC (Markov Chain-Monte Carlo) algorithm [26] was used to achieve high-resolution inversion and improve vertical resolution of inversion results. The deterministic seismic inversion can only identify about 10 m thick sand beds, but fail to identify thin sand beds or interbeds which are less than 10 m thick. In oilfield A, the target beds are mostly thin oil layers, less than 4 m thick, even less than 1 m, so low-resolution constrained sparse spike inversion can only reflect the overall trend (Fig. 9a, 9b), while the geostatistical inversion based on MCMC algorithm can effectively improve the vertical resolution, and show details of the reservoir (Fig. 9c, 9d).

(2) Threshold volume interpretation method was used to transfer the impedance inversion to lithosome, in order to improve the accuracy of interpretation. Affected by diagenesis and sedimentation, the seismic impedance would change vertically and laterally [27]. In continental region where facies change rapidly, lateral variation is especially obvious, resulting in the change of relationship between impedance and lithology. Lithofacies model is built by using sequential indicator simulation method (Fig. 11), by the constraint of the lithology interpretion of threshold (Fig. 10).

Traditional layering and single threshold lithology interpretation method can not deal with horizontal impedance changes caused by deposition, and the reservoir impedance characteristics of all wells can not be reflected just by one single threshold, resulting in high uncertainty of interpretation results. But the threshold lithology interpretation method adopt different thresholds in different facies belts, whose interpretation results consider more single wells, thus obtain more reliable results [27].

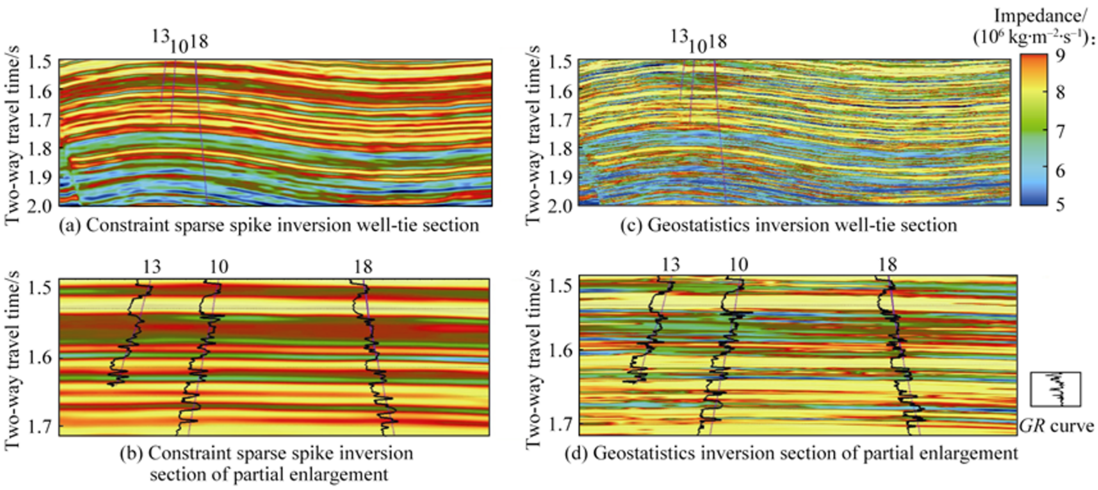


Fig. 9 Comparison between constrained sparse spike inversion and geostatistical inversion

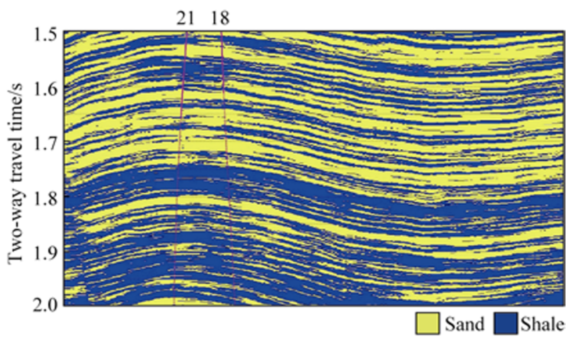


Fig. 10 Lithology interpretation results of threshold

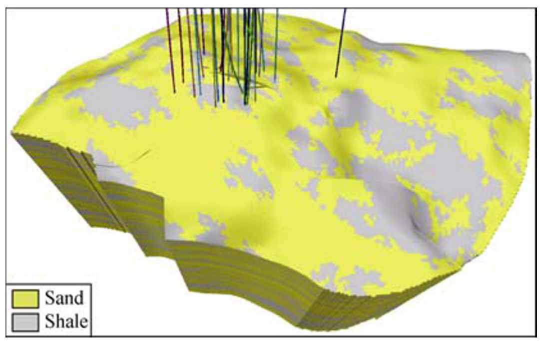


Fig. 11 Lithofacies model constrained by lithology interpretation result of inversion

3.2.2 Attribute modeling

Reservoir parameter models reflect its heterogeneity, i.e. the spatial distribution of internal physical property. Reservoir parameters mainly including porosity, permeability and oil saturation, etc, are important input parameters in reservoir numerical simulation, and directly affect the fitting results. In study area, impedance is well correlated to the porosity (correlation coefficient is 0.958). According to the idea of facies constraining modeling, impedance constraint and synergistic sequential Gaussian simulation methods were used jointly to build porosity model (Fig. 12), based on the pre-inversion constrained by lithosome. Then according to the analysis results of core, the correlation between porosity and permeability is established. The porosity model converted into permeability model (Fig. 13a). Finally, the classification J-function method was used to build oil saturation model [28] based on the mercury injection curve (Fig. 13b).

3.2.3 Model verification

Due to high offshore drilling cost, in order to lower development risk, multi-discipline data was used to build the geological model. Seismic forward modeling, comparison tests and reservoir numerical simulation were used to validate the model.

Comparison of the seismic forward modeling results of impedance model in the study area with the actual seismic section (Fig. 14), shows that the waveform of seismic forward modeling is consistent with the actual seismic waveform, indicating modeling constrained by impedance can effectively improve the reliability of model.

Since the stochastic simulation algorithm is a geostatistical interpolation method based on wells, the model is consistent with wells at the well points, while the crosswell prediction accuracy can be verified by rarefying wells. Fig. 15 is a through-well section of porosity model, in which Well 1 and 4 were involved in computation, the porosity values of model at the well points are similar with the actual porosity values, while Well 2 and 3 are not involved in computation (rarifying wells), so the porosity of these two wells are the predicted values by the model. It can be seen both thin and thick beds of the model are in good match with wells.

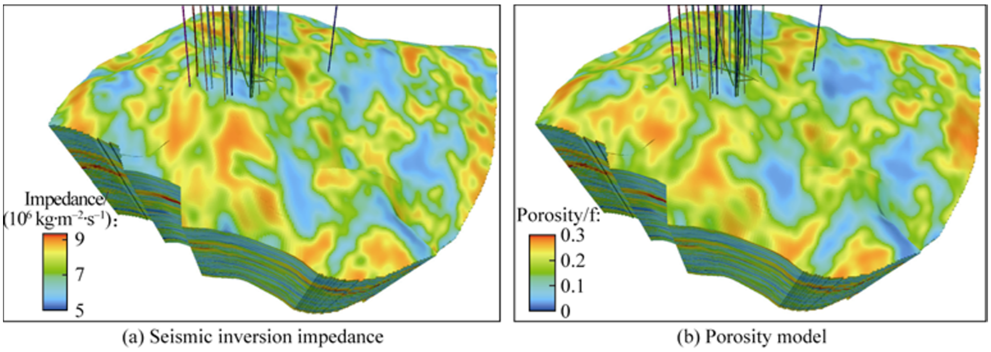


Fig. 12 Building of porosity model of study area

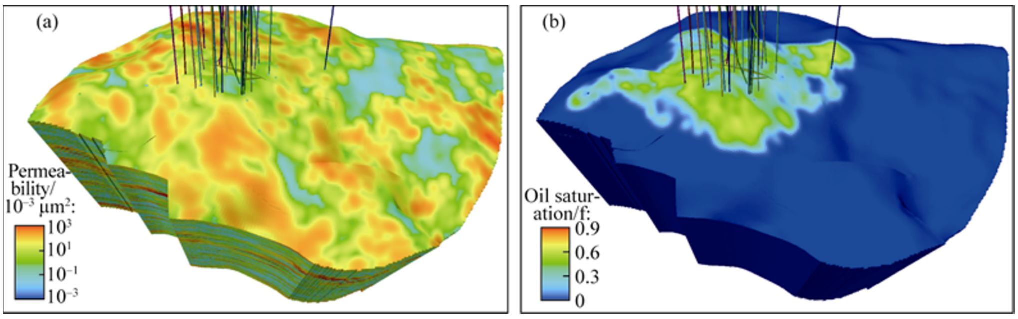


Fig. 13 Permeability model and oil saturation model of study area

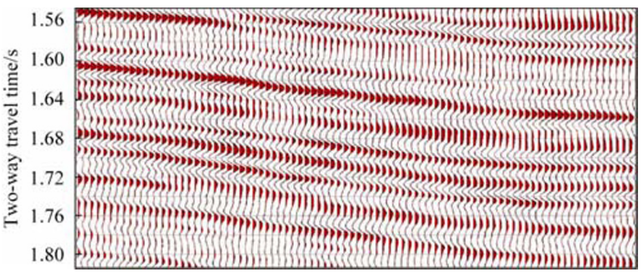


Fig. 14 Comparison between forward model (red) and the actual seismic section (black)

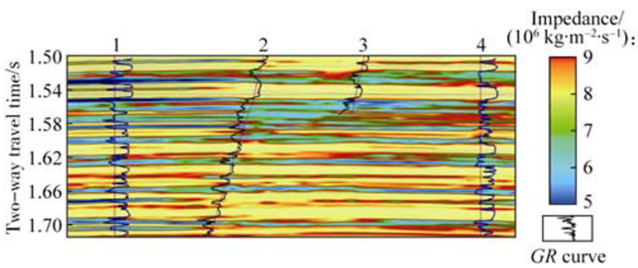


Fig. 15 Rarifying test of porosity model

Comparing the reservoir numerical results of reservoir numerical simulation history matching by modeling with the simulation results before modeling constrained, it shows the higher fitting degree in whole oilfield before manual adjustment, proving the accuracy of attribute model indirectly.

3.3 Modeling strategy constrained by “multi-level, multi-condition” seismic inversion results

The facies-contrained modeling usually involves two steps: (1) build the framework model, i.e. the lithofacies model; (2) build model of porosity, permeability and other attributes. Predecessors have made a lot of researches on lithofacies modeling constrained by seismic [24,29], and achieved some results in constrained attribute modeling [23,30–32]. This paper thinks lithofacies modeling and attribute modeling constrained by seismic data can improve the accuracy of the model significantly, that is “multi-level, multi-condition” constraint modeling (Fig. 17): in the first level constraint, dividing of lithofacies in single well is taken as the first variable, take lithology probability and the lithosome as the second variable in the exploration and development stages respectively to build lithofacies model (“multi-condition” constraint); in the second level constraint, lithofacies model is taken as the first variable, and impedance data is taken as the second variable to build porosity (property) model, constrained by impedance in horizontal and vertical direction (“multi-condition” constraint).

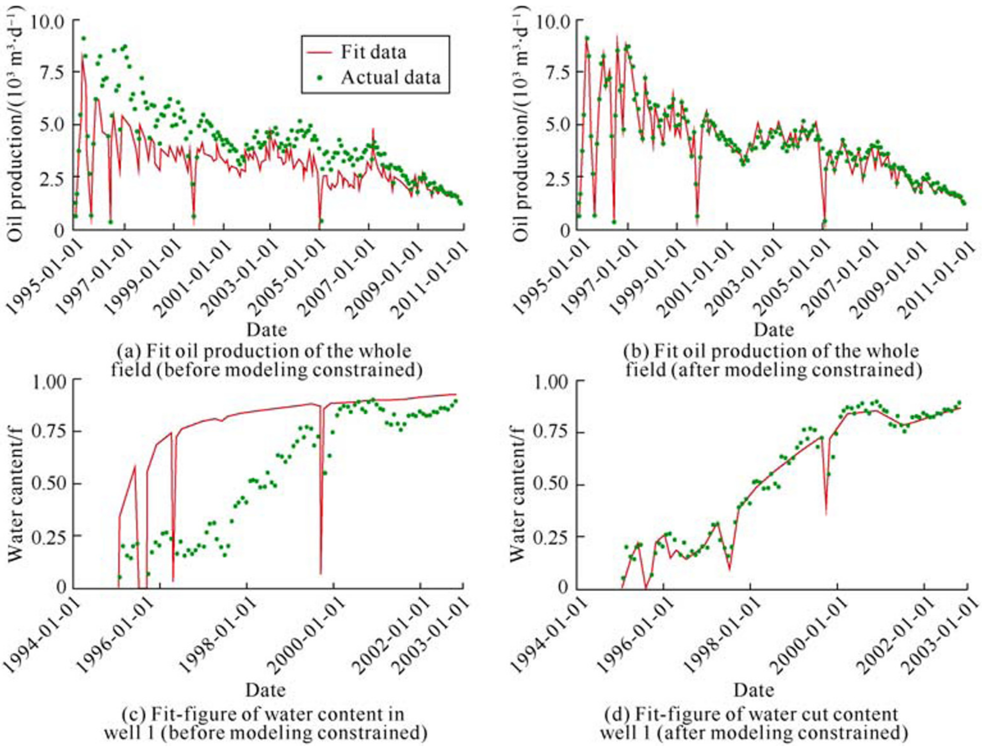


Fig. 16 Comparison of history match

Modeling examples in this paper indicate that the model built by using “multi-level, multi-condition” constraint has high accuracy, recovering the statistical pattern of input parameters. Besides, the forward result by model matches well with seismic on the macroscopic scale (Fig. 14), and well with data on the microscopic scale (Fig. 15). The method can effectively improve the accuracy of history matching (Fig. 16).

After constraint modeling, the results of numerical simulation of the study area are very well, because of high seismic data quality with 60 Hz dominant frequency wavelet, stable deposition, correlatable strata, stable barrier beds between oil layers, and no muddy intercalation. But for continental sedimentation system, the depositional environment changes rapidly laterally, frequent sand and shale interbed in vertical direction, such as in the lateral accretion body of river point bar, muddy intercalations are complex in distribution, and usually

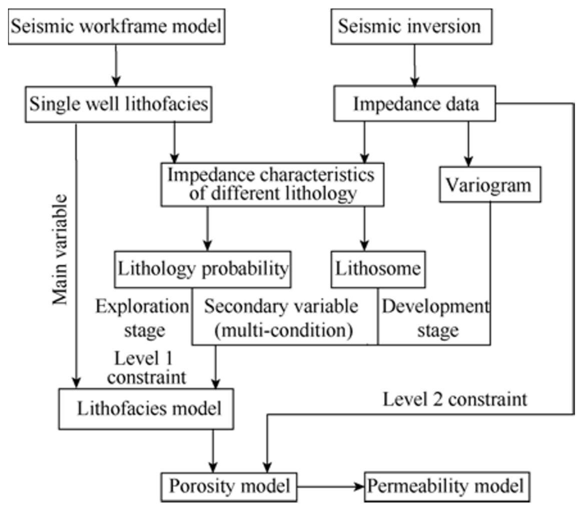


Fig. 17 Flow chart of “multi-level, multi-condition” modeling

less than 0.5 m thick. The accuracy of present modeling and inversion can only define the single sand body, interbed intervals are difficult to be described, adversely affecting waterflooding deployment. The application of research on interbed simulation is limited [33–34]. Generally, this kind of research requires outcrop survey and architecture study to modify the specific model.

4 Conclusions

Stochastic simulation featuring “mathematical reality” does not always reflect the “geological reality”. The research of seismic forward model indicates that geology modeling constrained by seismic inversion data can improve the accuracy of model. Wave impedance is more suitable to be used as constraint for geological modeling than other seismic attributes. The modeling constrained by “multi-level, multi-condition” seismic inversion results can take full advantage of seismic data, improve crosswell prediction accuracy of model, and match better with production performance.

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