Preparation and application of stochastic simulation for the sensitive parameters of oil-bearing reservoir

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Abstract. The petrol physical inversion, based on the parametric relations defined by the Archie’s formulas, revealed that oiliness of reservoir in the targeted zone increases along with the resistivity increment. Using the different values of resistivity $R_t$, and water saturation $S_w=80\%$ as the aqueous layer limit, we build up a theoretical chart of $R_t$ greater than 3.5Ω.m as the reference standard for Oil bearing sand body. Upon the statistical results of actual well data, we set “the cloud relationship” between $R_t$ and P-impedance under the constraint of geostatistics inversion data, and used the cooperative simulation algorithm to get a spatial prediction of oil-bearing sand body by means of inversion data of the P-impedance.

1. Introduction
The cloud concept is proposed by the academician of Chinese Academy of Engineering professor Li Deyi (1995). The study improved the deficiency of probability theory and fuzzy mathematics in processing uncertainty instance and integrated relevancy both of them¹. In the method, there is an assuming frequency distribution function $f(x)$ from some data attribute that collected data X is according to actual frequency distribution. The function generates several cloud stack of different particle size automatically. And the generated each a cloud represents a discrete and qualitative concept. That is cloud transform which maps from continuous numerical interval to that of discrete ones². Cloud transform set up a certainty model maps between qualitative value and quantitatives, which is a kind of nonlinear stochastic simulation. The cloud transform carries out mapping between the two variables in probability field, and follow the corresponding complex nonlinear relationship of the two variables.

Cloud model is characterized by a concept of three numerical variables overall, including Expectation, Entropy and Hyper entropy (figure.1). Expectation is the best representative of qualitatives or is quantified typical sample of the concept. Entropy is the uncertainty measure of qualitative concept, which reflected the acceptable cloud droplet value range in universe. Hyper entropy uncertainty measure of entropy representative of dispersion degree of entropy³.

For seismic reservoir attribute prediction in cloud transform, a cloud model is established among impedance and corresponding attribute parameters to solve functional relationship of linear dispersion and entirety attribute data. And the cloud model overcome the difficult problem of simple mapping among different kind of attribute data. The cloud model process may be enhance the reliability of predicted results⁴.

In stochastic simulation practical application, the cooperative simulation mostly build up the relationship among impedance and porosity, permeability, saturability as usual⁵. The parameters of porosity, permeability, and saturability, are all indirectly obtained by well logging evaluation. And the collected data may be affected by numerous factors within the following simulation process.
In order to keep integrity and objectivity of raw data, we directly used well logging as a origin data for cooperative simulating.

![Figure 1](image)

**Figure 1.** The illustration of basic concepts and definition of cloud model.

Archie’s formulas explicit that resistivity is the most sensitive parameter to oil-gas possibility, however, there are many combined influences from lithology and oil-gas bearing properties. The problems include that how to discriminate the characteristic parameters that merely rely on the oil-gas possibility, and how to set up the correspondence parameters to the geostatistic inversion pressure wave impedance. And then the parameters are used to valid combined the fine reservoir description, to deliberate well logging interpretation, oil and gas prediction with together, to predict oil bearing property of tight reservoir by seismic data. Focusing as above proposing, this is the underline introduce on the research approach and methods in the article.

2. **Preparation of oiliness sensitive parameter**

The resistivity is usually used to evaluate oil-gas possibility of reservoir in well logging. The resistivity magnitude is not only influenced by lithology itself, but fluid property in the pore. Archie’s formulas delivers the relationship among the reservoir porosity, fluid characteristics, and resistivity, and is given by

\[
F = \frac{R_o}{R_w} \frac{a}{\phi^m} \\
I = \frac{R_t}{R_o} \frac{b}{S_w^n}
\]

(1)

Where, $S_w$—water saturation, V/V, $R_w$—formation water resistivity, $\Omega$.m, $R_t$—formation resistivity, $\Omega$.m, $R_o$—formation resistivity of 100% water saturation, $\Omega$.m, $a$—porosity, $\Omega$.m, $b$—scale factor, $m$—porosity cementation factor, $n$—saturability factor.

Archie’s formulas also be able to written as

\[
R_t = \frac{a^*b^*R_w}{\phi^m * S_w^n}
\]

(2)

For the reservoir formation, the parameters, $a$, $m$, $n$, $R_w$, are fixed, once the reservoir fluid is determined ($S_w$ fixed), the congruent relationship of formation resistivity $R_t$ and porosity $\phi$ may be established, while in well logging interpretation, usually used acoustic interval transit to calculate reservoir porosity $\phi$, and it is given by

\[
\phi = \frac{\Delta t - \Delta t_{ma}}{\Delta t_{f} - \Delta t} \frac{1}{v_p} - V_S h \frac{\Delta t_{sh} - \Delta t_{ma}}{\Delta t_{f} - \Delta t_{ma}}
\]

(3)
Δt—rock interval transit time, μs/ft, Δt_{ma}—rock matrix interval transit time, μs/ft, Δt_{f}—fluid interval transit time, μs/ft, Δt_{sh}—mudstone interval transit time, μs/ft, V_{sh}—shale content, V/V, C_{p}—compacting factor.

According to formulas (2) (3), measured acoustic interval transit time, based on Archie’s theories and formulas, rock Volume model theory, forward modeling of reservoir rock physics can be carry out\[^7\]. Suppose the fluid properties are different, and S_{w}=20\%, 40\%, 60\%, 100\%, are represent respectively the transformation of fluid properties from oil to water in reservoir space.

Figure 2 shows the variation trend of resistivity under different fluid types (S_{w} different) in the actual pore space simulated by forward petrophysical modeling (measured by AC curve). Figure 2 explained that under the condition of same pore (acoustic time difference), the resistivity increases significantly with the decrease of water saturation, suggesting the influence of fluid on the resistivity under the condition of the same physical property. However, under the same water saturation condition, the porosity decreases and the resistivity increases significantly, indicating that the physical property has an impact on the resistivity when the fluid properties are consistent. Theoretically, the increase of physical density and oil content will lead to the increase of resistivity, but the change is in line with a certain change trend.

![Figure 2](image-url)

**Figure 2.** Crossplot of simulated resistivity and acoustic interval transit time based on Archie theory.

Taking the actual production well F27-4 as an example, the trend of the intersection diagram of resistivity and acoustic time difference (figure 3, left) is very consistent with the Archie theory trend shown in figure 2, except that the resistivity is significantly higher in the red area. Referring to the existing production data, the well logging curves of tested pay layers (right of figure 3) are combined with the crossplot, and it is found that three oil test reservoirs with a daily oil output of 9.96t are all within the red range of the relatively high value zone. While, in the crossplot, selected all the regions with higher resistivity values deviating from the trend obviously (red circle on the left in figure 3) contrast to all the oil pay formations in the logging curve, as well as some untested formations which the saturation interpretation results pretty good for oil reservoirs and some poor oil reservoirs, the dry layer was not included.

This study statistics the production data of the multiple wells and well logging curve, confirmed that the interval of interest in the study area are characterized by high resistivity, once bearing oil of the formation of reservoir its resistivity will deviate from the basic skeleton of Archie theory trend, this is the typical characteristics of the oil layer, and the key to choose the difference of resistivity R_{t_f} as sensitive parameter for reservoir prediction oiliness.
In order to quantitatively represent the deviation value of resistivity after reservoir containing oil, used Archie formula (1) and porosity calculation formula (3), take 80% water saturation as limit of water layer, to calculate the theoretical formation resistivity \( R_{t0.8} \) (4), under conditions of the formation and \( S_w=80\% \). So that, the \( R_{t0.8} \) parameter includes the lithology and physical properties of the reservoir as well as the resistivity value when the reservoir fluid is formation water.

\[
R_{t0.8} = \frac{abRw}{\phi^m \sigma^n} \tag{4}
\]

When the reservoir contains oil and gas, according to Archie theory, the true formation resistivity \( R_t \) value of the actual formation must be greater than \( R_{t0.8} \), then the difference between the two values reflects the increment of the resistivity caused by the oil content of the reservoir. Based on this analysis, the resistivity difference \( R_t \) parameter (5) is introduced to represent the oil and gas resistivity of the reservoir. This parameter eliminates the influence of the lithology and physical properties of the reservoir on the resistivity and highlights the influence of the oil and gas resistivity on the resistivity.

\[
R_{t} - R_{t0.8} = \text{Resistivity difference} \tag{5}
\]

\( R_t \)—resistivity, \( \Omega.m \), \( R_{t0.8} \)—resistivity under condition of water saturation 80\%, \( \Omega.m \).

In figure 4, the scatter point is the intersection diagram of resistivity and acoustic time difference of multiple wells in the work area. The red line represents the trend line of \( R_{t0.8} \) (water layer trend line), and the area above the red line is the oil-gas layer with resistivity greater than \( R_{t0.8} \). The greater the point value deviation, the greater the resistivity difference \( R_t \), and theoretically the better the oil content.

3. The establishment of cloud relationship

Formula 2 and Formula 5 are used to calculate the resistivity difference \( R_t \) of each well. The \( R_t \) intersection diagram (figure 5) of the difference between \( P \)-impedance and resistivity was established based on the statistics of 112 layers in Wells near the seismic acquisition years. At the well point, the two are obviously correlated, and their variation range is relatively wide. The \( R_t \) value in each longitudinal \( P \)-impedance range is normally distributed, meeting the characteristics of "cloud relationship". \( R_t \) and resistivity difference is greater than 3.5\( \Omega.m \) above, corresponding to the explains of pay and poor layers, below 3.5\( \Omega.m \) basically for dry layer. That suggest the established cloud relationship between \( R_t \) and \( P \)-impedance may be used to identify the reservoir’s oil-gas characteristics.
4. Cooperative simulate reservoir oil bearing prediction

Only the "cloud relationship" between resistivity difference $R_t$ and P-impedance cannot complete the oil-bearing prediction of reservoir, and lithology body and P-impedance body are needed to realize it.

Geostatistical inversion bases on Markov chain - Monte Carlo algorithm that uses the analysis of the well data and geological information. The analysis process is achieved by getting the probability distribution function and variation function, correct sample set for statistical significance, at the same time with seismic data as constraints on the space, the addition of logging information makes plenty of details of more than seismic data bandwidth. All above per-treatments ensures that the inversion results with high resolution of the lithologic body to reconstruct the real reservoir characteristics. Therefore, this method can achieve fine characterization of thin interbed reservoirs, complex lithology, and dense well pattern reservoirs [8-11], with very high accuracy of characterization.

In the process of solving, all kinds of data are ready, some key technologies are needed to control the rationality of the prediction results.
Firstly, it is necessary to restrict the lithologic body and control the parameters so that the co-simulation can only be carried out in the sandstone region. This technique is also known as "lithologic shielding" technique \cite{12}.

Secondly, it is necessary to establish "cloud relationships" of different longitudinal units (figure 6). The division of longitudinal units and the morphological characteristics of "cloud relationships" are the main basis, which usually consulted geostatistic inversion division results of longitudinal units. Co-simulation is a kind of random simulation, which also needs to be constrained by probability density function and variational function in space. Therefore, reasonable rate density function and variational function need to be prepared for different longitudinal elements, and the Rt data volume of resistivity difference value is finally obtained. Obtaine the Rt data body is only the implementation of the co-simulation data body completed. Finally still need to construct oil sands body depict boundaries of the Rt according to the figure 4, to more than 3.5Ω.m for the standard oil sand body space distribution.

In the co-simulation, the well only provides the "cloud transformation" relationship and does not participate in the simulation. Therefore, the production data at the well point and the actual interpretation results can be used to prove the rationality of the simulation results. It can be seen from the superposition diagram of the co-simulation profile and well data that the consistency between the simulation results and the fine interpretation conclusion of well point logging can reach more than 95%, and all is the simulated oil-bearing reservoirs is pay in the actual production. Taking Wells F27-4, W19-X29 and W23-X25 as examples, well logging evaluation results and actual production data indicate the rationality of the simulation results and verify the feasibility of the co-simulation method in predicting oil-bearing reservoirs (figure 7, Table 1).
5. Conclusions
The resistivity of the reservoir increases significantly after oil is bearing, and there is a clear "cloud relationship" between the resistivity difference $R_{t}$ and the P-impedance, which is a prerequisite for the application of the co-simulation method to predict the oiliness of the reservoir;

Before the co-simulation is carried out, the reservoir characterization depict of geostatistical inversion must be completed to provide "lithologic shield" and P-impedance data for the co-simulation;

The co-simulation technology effectively combines the post-stack geostatistical inversion results with the resistivity difference $R_{t}$. The inversion results show the obtained the spatial distribution characteristics of the oil-bearing body through "cloud transformation". The researches have used the production and logging interpretation data and the research results are verified reliable. The co-simulation technology provides a basic method and basis for the exploration and development of oil fields.

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