Ranking Geostatistical Reservoir Models with Modified Connected Hydrocarbon Volume

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Abstract A large number of realizations can be created relatively quickly with geostatistical tools. Flow simulation of all the realizations is challenging because of computational time requirements. Often, a limited number must be selected for input to flow simulation. Selecting the first realization or selecting them randomly may lead to unusual low or high results and does not permit an assessment of uncertainty. The realizations are ranked according to some simple measure that (ideally) is highly correlated to the flow response variables of interest. A new static ranking measure of quality Q_s is proposed. This measure is the hydrocarbon volume connected to the well locations and modified by additional factors. The modifying factors include the distance from each cell to the nearest production well and the geometric average permeability of the cells between the cell and the nearest production well. A program is presented to calculate Q_s from three-dimensional realizations of cell volume, porosity, permeability and water saturation. A simple example shows how the program works.
Keywords: Ranking; Realization; Connected hydrocarbon volume; Geostatistics

Introduction

Reservoir performance prediction usually involves the two-step process of static property modeling followed by flow simulation. Geostatistical techniques are used to build static property models based on all available data and geological interpretations (Journel, 1990; Journel and Alabert 1990; Haldorsen, 1990). There is unavoidable uncertainty in the geological model and alternative scenarios should be considered. A set of scenarios can be formalized and a number of realizations need to be constructed for each scenario (Deutsch, 2005). A large number of realizations may be created quickly with modern modeling software. The geological uncertainty is characterized by the differences between many equal probability reservoir models and need to be transferred to the uncertainty in production forecasts. However, in practice, only a limited number of realizations will be chosen for flow simulation because of computational costs associated with multiple detailed flow simulations. Randomly choosing a limited number of

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realizations will not accurately represent uncertainty. Ranking could be used to select these models which will produce expected and bounding flow results (Deutsch and Srinivasan, 1996).

The idea of ranking stochastic realizations was first published in the context of geostatistics in 1992 (Ballin et al., 1992，1993). Ballin suggested the use of a fast simulator as a surrogate for a comprehensive flow simulation. Similar idea has been adopted to rank multiple realizations (Saad et al., 1996; Gilman et al., 2002; Ates et al., 2003). Kupfersbergera and Deutsch (1999) chose a limited fine scale realization for flow modeling based on ranking result of coarse scale realizations. All the coarse realizations are used for flow simulation and then ranked according to aquifer responses. An another way of ranking is to exploit relatively simple geological measures to accurately select realizations that correspond to low, median, and high production responses (Deutsch and Srinivasan, 1996). The advantages in ranking geological models for fluvial reservoir using static methods and dynamic methods are discussed by AI-khalifa (2004). This paper will focus on geological static measures. In order to select geological realizations correctly, the ranking measure must be highly correlated to the production response.

Ranking realizations by original hydrocarbon (oil or gas) in place (OOIP) is a reasonable first approximation（Tang and Liu, 2008）. Reservoirs with more hydrocarbons will likely have higher production. The connectivity can also be accounted for, which is defined as the proportion of connected net reservoir volume and connected to wells (Laruel and Hovadik, 2006). Ranking could be based on connected hydrocarbon volume in place (CHV). Only the cells connected to production wells are counted. Experience has shown that including additional modifying factors improves the correlation between the ranking measure and important flow responses. Permeability is an important parameter for oil production; higher permeability permits higher production rates. The distance from any particular cell to the production well is also important; the hydrocarbon in closer cells will be produced first and is likely to follow a less tortuous path. These factors (and others) can be used as modifying factors in the calculation of CHV. A new ranking measure, static quality (Q_s), is proposed based on CHV by adding two factors, distance and permeability. The steps of ranking realizations based on Q_s are summarized. The ranking measure is static in the sense that no flow simulation or dynamic response is calculated.

A simple 2-D reservoir model with 6400 cells is built and 50 realizations of porosity, permeability and water saturation are constructed by sequential Gaussian simulation method (Deutsch and Journel, 1998). Flow simulation has been done for all 50 reservoir models with Frontsim module in Petrel modeling software. The final goal of a reservoir numerical simulation study is usually production forecast, which is expressed in terms of some performance parameters like cumulative oil production, oil recovery, water cut, breakthrough time, etc. The parameter of cumulative oil production is chosen for the ranking results of CHV and Q_s to be compared. Finally, some conclusions are presented.

Static Quality for Ranking

The static quality, QS, for a particular realization is calculated as follows:

$$Q_s = \sum_{iw}^{nw} \sum_{j=1}^{n_{iw}} V_j \cdot \phi_j \cdot \left(1 - S_{w,j}\right) \cdot \left(\frac{d_{\max}}{d_{j,iw}}\right)^{dw} \cdot \left(\frac{k_{j,iw}}{k_{\max}}\right)^{kw} \qquad (1)$$

Where Q_s is the static reservoir quality for a particular well distribution and geological model, n_w is the number of producing wells, V_j is the volume of cell j that is close to well i_w, ϕ_j is the porosity of cell j, $S_{w,j}$ is the water saturation of cell j, $d_{j,iw}$ is the distance of cell j to well i_w , d_{max} is the upper limit of $d_{j,iw}$ and the cell will not be calculated if it is beyond this value, $k_{j,iw}$ is the geometric average of the permeability from cell j to well i_w in the shortest path, k_{max} is the upper limit of $k_{j,iw}$ that means $k_{j,iw}$ will be set to k_{max} if it is beyond $k_{j,iw}$. For simplicity of notation, the realization number is not indexed in Equation 1.

The well locations and types must be known. The calculation of Q_s, only considers those cells connected to the production wells. The oil in cells not connected to any production well will not be produced; therefore, it should not be considered in ranking. The specific well locations have a big effect on Q_s. Different well configurations will activate different cells and change Q_s. In general, including this specific information in ranking will lead to much improved ranking relative to some general ranking measure that does not consider the well locations.

The connected cells to each well are calculated by geoobjects. Most commercial software includes this calculation. A public domain program Geo_obj was developed to calculate the geoobjects from three-dimensional porosity, permeability and water saturation models (Deutsch, 1998). Prior to calculating geoobjects, thresholds for porosity, permeability and water saturation are needed to code the cells as reservoir or not. The thresholds are based on experience with reservoirs of the same type, production data or calibration with flow simulation. If the threshold values are difficult to determine, then a sensitivity study may be required. A binary net indicator is established according to whether the cell is reservoir or not. The basic idea of Geo_obj program is to scan the three-dimensional net indicator array aggregating those cells that are connected. More details can be found in Deutsch (1998).

The workflow of calculating Q_s is illustrated as figure 1.

The ranking steps can be summarized as follows:

1. Assemble multiple realizations of reservoir properties including porosity, permeability and water saturation. The net indicator will be calculated according to the chosen threshold values.
2. Calculate geo-objects (connected three-dimensional sets of geological objects). The connected cells have the same geo-object number. Fig.1

shows a simple illustration of two geo-objects, and they are separated by non reservoir.

3. Sequentially select an unsampled cell j.
4. Judge net to gross (NTG) of the cell j which is 1 or 0. If it is 0, then go to step 3. Otherwise, go to next step.
5. Find out the well i_w which is closest to cell j. Judging if the well i_w and the cell j are connected, if they are not connected, finding out the second closest well and then do the same judgment. Otherwise, go to the next step. Taking cell i as an example, the closest well to the cell i is the well i_w, but they are not connected, so the well j_w will be selected.
6. Calculate the shortest distance between the well i_w and the cell j, and the geometric average permeability along the line of sight from the well i_w and the cell j. As shown in fig.1, although the distance between cell k and well i_w is the same as the distance from cell j to well i_w, the geometric average permeability along the line from one cell to one well is different because of the existence of shale zone. The cell j would be more important than the cell k due to the contribution to well i_w.
7. Calculate the Qs for the well i_w and the cell j, then repeat step 3 to 7 till the Q_s for the last cell is calculated.
8. Rank realizations based on Q_s.

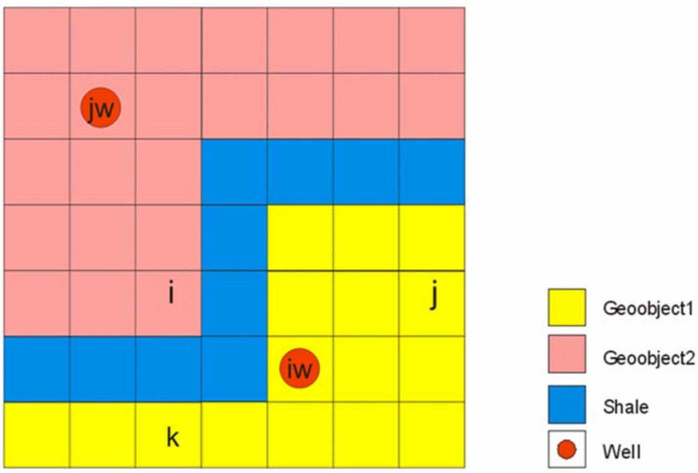


Figure 1 Geo-object

A FORTRAN implementation of this method is coded in program RANKING. This program was modeled after GSLIB programs.

Compare with CHV

CHV is a popular measure used to rank realizations. We compare the ranking results using CHV and Q_s. As shown in fig.2a and fig.2b, the reservoirs in both cases have the same petrophysical attributions except the location of wells. In case one, there is one well at each side of the shale zone. In case two, the two wells are at the same side of the shale zone. For CHV, we can see there is no difference between case one and case two. On the other hand, there is bigger Q_s value in case two than case one. So, Q_s can tell the difference between the two cases, but CHV can not.

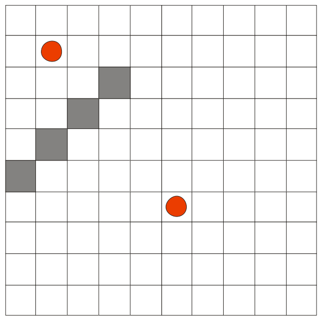


Figure 2.a Wells location case 1

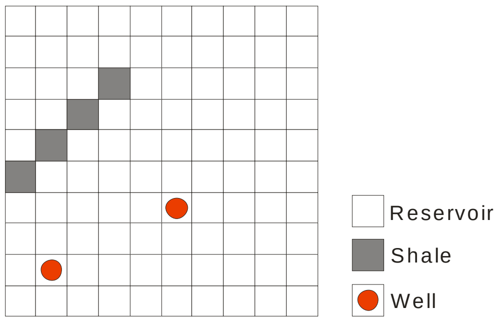


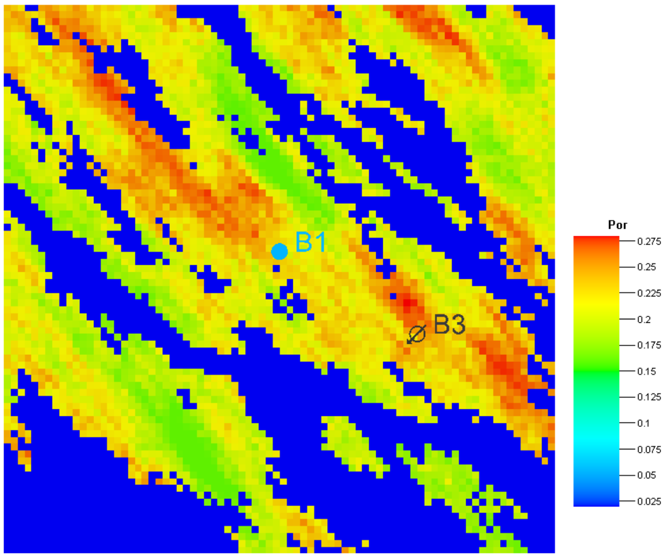
Figure 2.b Wells location case 3

Table 1 Comparing results

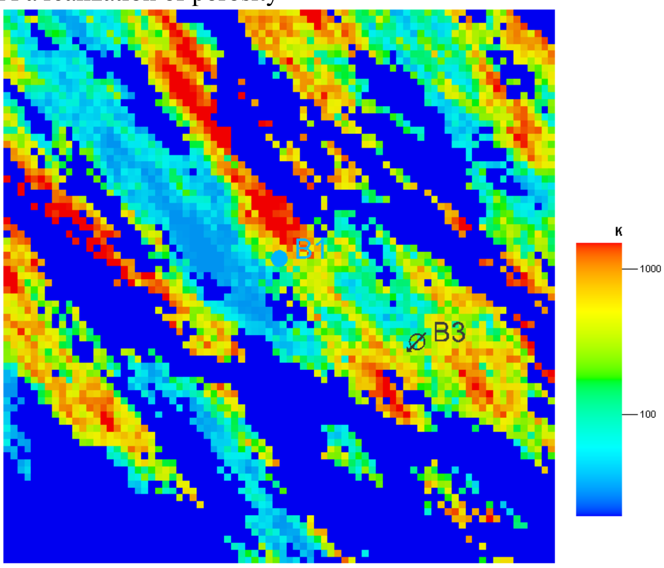
	Case1	Case2
CHV	5373.00	5373.00
Qs	828.89	818.79

A Simple Example

Consider a simple two-dimensional example to show how the program works. The grid is 80×80. There are two wells, one production well and one water injector. Figure 3 shows one realization of 50 of porosity and permeability models. We use sequential Gaussian simulation method to build these realizations with an anisotropic variogram. Program RANKING was run with all 50 realizations. Table 2 shows the ranking result. The first and fourth column are the number of realizations and the column of Q_s and CHV are the ranking order according to static quality of reservoir and connected hydrocarbon volume respectively.



A a realization of porosity



B a realization of permeability

Figure 3 One realization

From table 2, we can see the realization 3, 21 and 42 represent P10, P50 and P90 of Q_s. The realization 26 is highest ranking realization and realization 40 is the lowest one. The correlation between CHV and Q_s is established, as shown in

Figure 4. The correlation between CHV and Q_s is low because the distance and permeability get big weights and it will become higher as weights decrease.

Table 2 Ranking result

Number	Qs	CHV	Number	Qs	CHV
1	30	14	26	50	50
2	16	43	27	4	9
3	5	21	28	26	4
4	44	25	29	8	12
5	41	38	30	14	23
6	3	3	31	10	18
7	27	16	32	12	2
8	7	31	33	23	49
9	48	20	34	17	26
10	29	17	35	28	1
11	39	36	36	2	29
12	42	42	37	40	30
13	49	46	38	34	34
14	43	7	39	18	6
15	46	37	40	1	10
16	15	24	41	20	27
17	38	33	42	45	15
18	35	45	43	47	47
19	6	5	44	37	44
20	31	19	45	33	32
21	25	48	46	9	41
22	13	28	47	22	39
23	32	35	48	11	8
24	24	40	49	36	11
25	19	22	50	21	13

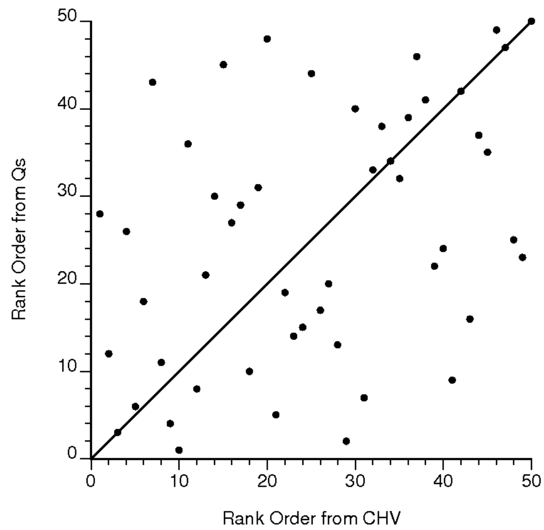


Figure 4 Correlation between Qs and CHV

In order to check the reasonability of ranking results based on Q_s, flow simulation using Frontsim module in Petrel software for all 50 realizations are performed. Figure 5 shows cumulative oil production in each year from 2008 to 2017.

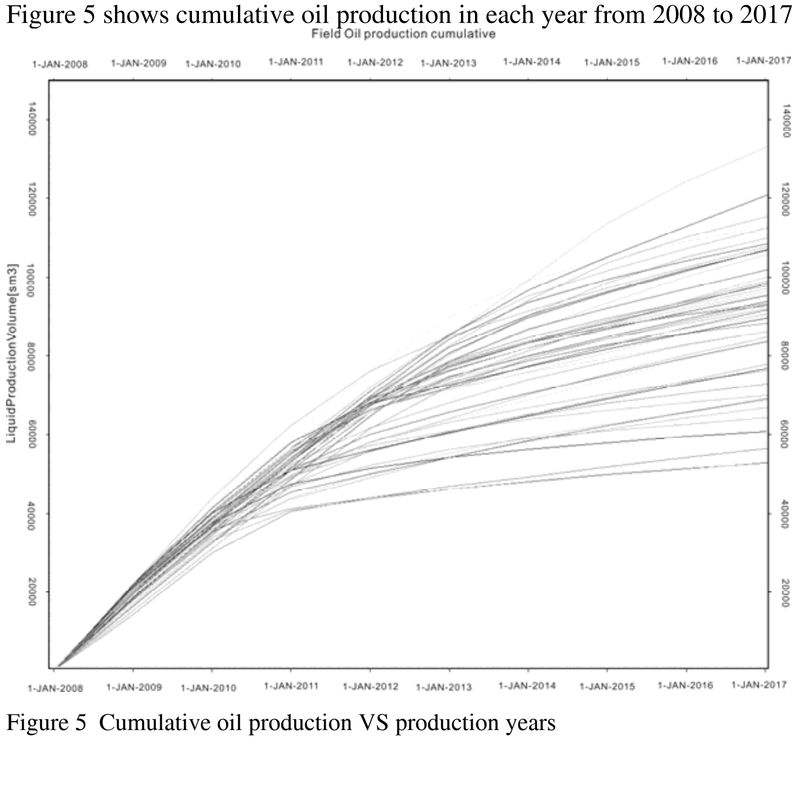


Figure 5 Cumulative oil production VS production years

Using COP (cumulative oil production) in early development period as response value, 50 realizations are ranked and the result is compared with ranking result from Q_s. As shown in Figure 6, the correlation between flow simulation response and Q_s is 0.873. The correlation between CHV and COP is also established and its value is 0.553 (Fig.7). So, Qs is better than CHV to rank realizations in the early oil production period.

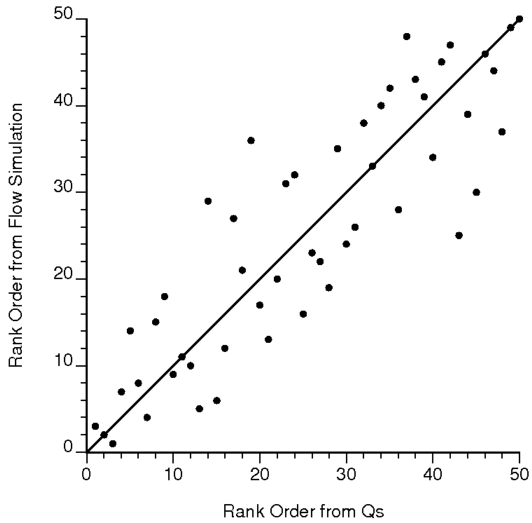


Figure 6 Correlation between Qs and COP

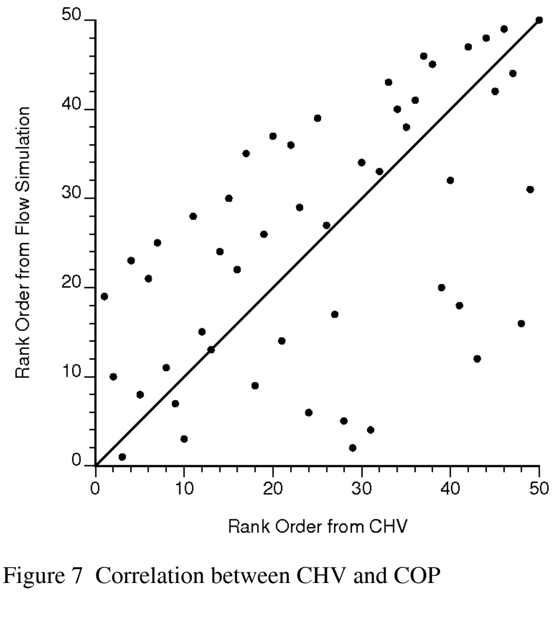


Figure 7 Correlation between CHV and COP

Conclusions

A new ranking measure Qs based on CHV is proposed. The Qs is better than CHV because it considers the influence of permeability and distance of productive cells to those production wells, moreover, the configuration of production wells is also considered. Oil in cells which are farther from production wells are more difficult to be produced. The average permeability along cells to production wells is higher and the oil in those cells is easier to be got. The weights in formula 1 will affect the ranking results. The weights of permeability and distance are smaller and the correlation between Qs and CHV is higher. A case study shows that there is a high correlation between Qs and flow simulation response, cumulative oil production, in the early period. As the oilfield is developed further, the correlation will become lower because more and more oil will be produced and the effect of permeability and distance will become less, especially in the oilfields of injection water development.

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