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On the Optimal Well-Placement Based on One-Dimensional Data from a Single Well

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The most common geostatiscal approach for well placement in SAGD is three dimensional (3D) modeling of the reservoir. This study is to apply one dimensional data (well log data) to quantify oil recovery, and to place the production well at its optimal location. Reservoirs with higher probability of good recovery are the main target in this work. The limited information provided by well log data is used to predict the lateral size and position of the barriers in order to avoid them for the drainage recovery process. An optimized estimation of the barriers in such cases will result in optimal well placement. This work basically concentrate on a few properties of barriers and disregard some properties such as tortuosity (would not be calculated by one-dimensional data) and suggest a Monte Carlo approach for barrier prediction. The calculation of the recovery-versus-depth plot is explained as well. We use limited data to extrapolate crucial information. The main goal is to quantify the recovery expectation without involving (3D) modeling of the reservoir. This approach can later be applied on a larger scale to data from multiple wells.

Introduction

In the application of SAGD, well placement is the most important consideration and requires detailed knowledge of the reservoir. Placing the production well at the proper location and depth could strongly influence the final recovery. The reservoirs considered for well-placement and recovery process are the so-called "good" reservoirs, containing $70-80\%$ net-to-gross (NTG) ratios. The recovery process and well-placement should avoid the barriers and maximize recovery based on limited information from several or even one set of well log data. This study focuses on the assessment of the expected recovery using limited knowledge of one dimensional, single well log data of a reservoir.

When deciding on well placement, the most common practice is goestatistical 3-D modeling of the region (i.e. accounting for the vertical as well as lateral positions of the barriers) before making calculations of recovery and optimal well-placement. This often requires much data and very intensive computations. In contrast, analysis based on a one-dimensional approach (e.g. based on a single set of well log data) should be computationally effective, but naturally with more uncertainties. The missing information in such one-dimensional approaches can be compensated by correlations such as those between the thickness and the areal extension of the barriers.

Our ultimate goal is maximum recovery. The net-to-gross ratio in the reservoir is just one parameter for recovery determination; there are a few other characteristics regarding the net (non-net) reservoir which can significantly influence the final recovery. The continuity of the barriers, their positions, orientations, tortuosity, and the vertical depth of the barrier from the surface of the reservoir can strongly affect the flow rate, well placement and recovery. To consider each one of these properties in recovery analysis will quickly result in computation complexities that are unmanageable. Here, to reduce the compu-

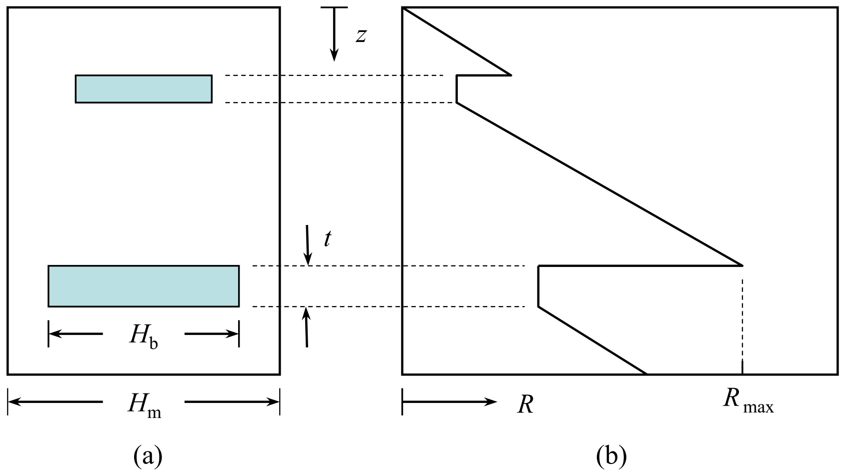

Figure 1: Model (a), expected recovery (b).

tational complexity, some knowledge such as tortuosity factor would not be provided in the one dimensional well-data. As we showed in [1], no correlation between the size and tortuosity, or between thickness and tortuosity, could be detected. Therefore, it may be possible to determine well-placement even if some important characteristics of the barriers are disregarded.

In this paper, we first outline the 1-D methodology using Monte Carlo technique. We will then apply this simplified approach to a case involving two barriers of known depths and thicknesses. The lateral extensions (H_b) and position (l_c) of these barriers are, however, allowed to have statistical variations. The uncertainties in H_b and l_c will be incorporated into the final estimation of oil recovery – a quantity that we will call the *statistically-averaged* recovery.

One-Dimensional Analysis

This analysis is for estimating the expected recovery from a reservoir based only on limited knowledge of the depths and the thicknesses of barriers at one specific location (e.g. data from a single borehole). In this approach, the recovery estimation is carried out by assuming a simplistic picture that the barriers can have random vertical and lateral positions as shown in Fig. 2. We will assume that barriers which exist at any depth will have a finite probability of being detected by the borehole. The probability of detection will depend on the lateral position l_c and lateral extent H_b of the barriers, both of which are treated here as random variables. The other two variables associated with the barriers, namely the depth z and the thickness t, as assumed known with no statistical variations. To determine recovery, we will assume that a production well placed at a given depth is capable of recovering all oil above it, except for the volume that is situated directly above a barrier. We also assume that the oil is distributed evenly over the net region, and so the recovery could be represented by the volume of the net region that is accessible to the production well (i.e. region that is not blocked by barriers). We will denote recovery by the symbol R, and since R is represented

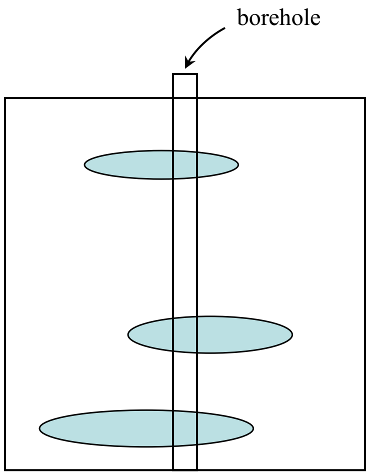

Figure 2: Positioning of barriers inside the model.

by a volume, it will have units of m^3. According to the above assumptions, a typical plot of the recovery R versus the well depth z will appear as in Fig. 1 which demonstrates the corresponding 1-D representation of the model region. Clearly, well placement should be made at a depth that corresponds to maximum recovery R. Note that as the production well depth reaches a level which coincides with the top of a barrier, there will be a sudden decrease in production as oil drainage will be blocked, thus leading to a "step back" as shown. The magnitude of this "step back" will be determined by the average size of the barrier which, in a statistical sense, is equivalent to the *probability* of the barrier (as will be explained later). Because of the "step backs," the point of maximum R is not necessarily at the bottom of the model. This is the case shown in Fig. 1.

The R vs z plot can be understood as follows: Starting from the surface (at $z = 0$), the recovery increases linearly with the well depth. This is because we have implicitly assumed a constant model cross sectional area that is given by H_m. As such, the volume accessible to the production well would just be proportional to the depth. This is so until the well reaches the top surface of a barrier, at which point the accessible volume decreases abruptly because the oil above the barrier can no longer be recovered by gravity drainage. The amount of this "step back" to the left depends on the areal extension of the barrier. (To keep the scheme simple, the amount of recovery stays unchanged from the top of the barrier to the bottom, assuming no production well would be placed over the extent of the barrier thickness.) As the production well clears the bottom of the barrier, the recovery will again go up linearly, with the slope being inversely proportional to the corresponding cross sectional area. This process continues until the bottom of the model is reached.

We now need to evaluate the amount of "step back," which reflects the amount of inaccessible oil due to the size of the barrier. As explained earlier, this barrier size is more properly interpreted as a *probability* of occurrence of a barrier. This probability is calculated as follows: As shown in Fig. 3 , a barrier is characterized by its thickness t, lateral size H_b, and the lateral position of its centroid l_c (measured from the left). The variables t and H_b are correlated as shown in Fig. 4. As can be seen, the correlation is

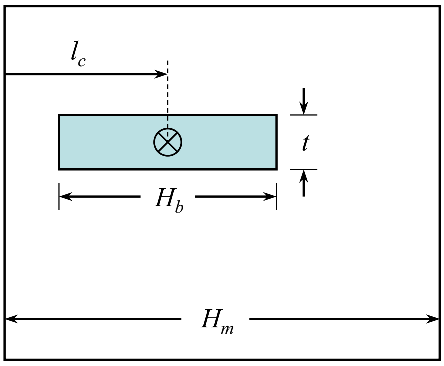

Figure 3: Characteristics to define a barrier.

a linear line given by the relation $y_{\text{fit}} = 40x + 10$ which minimizes $\sum(y - y_{\text{fit}})^2$, where $\sum \Delta y = 0$. Every lateral extension H_b is assumed to have a normal distribution around its mean ($m = y_{\text{fit}}$). The standard deviation for every barrier (Δy_i) is

$$\sigma = \sqrt{({y_i}^2 - \Delta y^2)/(N-1)},$$

which is about 30 for this particular data. As such, the quantity H_b is treated here as a Gaussian random variable with mean value m and standard deviation σ.

The lateral position l_c is another random variable which we will assume here to be *uniformly distributed*, i.e. it is equally likely to take on any value between 0 and H_m. Next, we determine the probability of occurrence of a barrier. A barrier "occurs" if it crosses the centreline of the model and is detected by the borehole. This (indicator = 1) will happen if

$$\begin{cases} l_c \le H_m/2 \;\; \text{and} \;\; l_c + H_b/2 \ge H_m/2 \;\; \text{or,} \\ \\ l_c > H_m/2 \;\; \text{and} \;\; l_c - H_b/2 < H_m/2. \end{cases}$$

The probability of occurrence is calculated using a Monte Carlo approach: A number of random trials (10,000 trials) were drawn for H_b, which followed a Gaussian distribution, and l_c, which was uniformly distributed. For every trial, the above "occurrence relations" were invoked to determine if the barrier were intercepted by the borehole. The final probability P_b was simply the ratio of the number of detections to the total number of trials, i.e.

$$P_b = \frac{\text{number of detections}}{10,000}.$$

The P_b evaluated as such can be interpreted as the *fractional occupancy* of the barrier

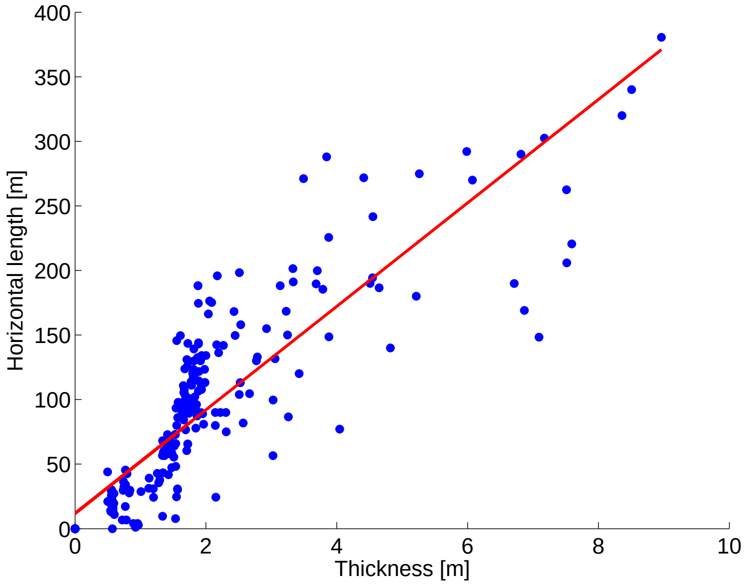

Figure 4: Lateral extension of barriers versus thickness.

within the model – in a statistical sense, i.e.

$$P_b = \frac{< H_b >}{H_m},$$

where $< H_b >$ is the average lateral size of the barrier. Finally, the magnitudes of the step-backs in Fig. 1 are given by

$$\text{step back} \equiv < H_b > \Delta z$$

where Δz is the vertical gap width between the present barrier and the one above it.

Table 1: Depth data for Fig. 5.

Barrier Depth	Barrier Thickness
9	3
17.5	4.2
33.5	5

Results and Discussion

As a result of uncertainty in lateral size and position of barriers, the evaluation of recovery is not unique for the reservoir. Based on the configuration of barriers and their thicknesses, there might be cases in which the maximum recovery happens at a location which is not similar to the other case. Obviously, the production well is placed at a depth that corresponds to maximum recovery R. However, due to different "step backs," the optimal well placement would vary from case to case. This behavior is shown in Fig. 5 which clearly

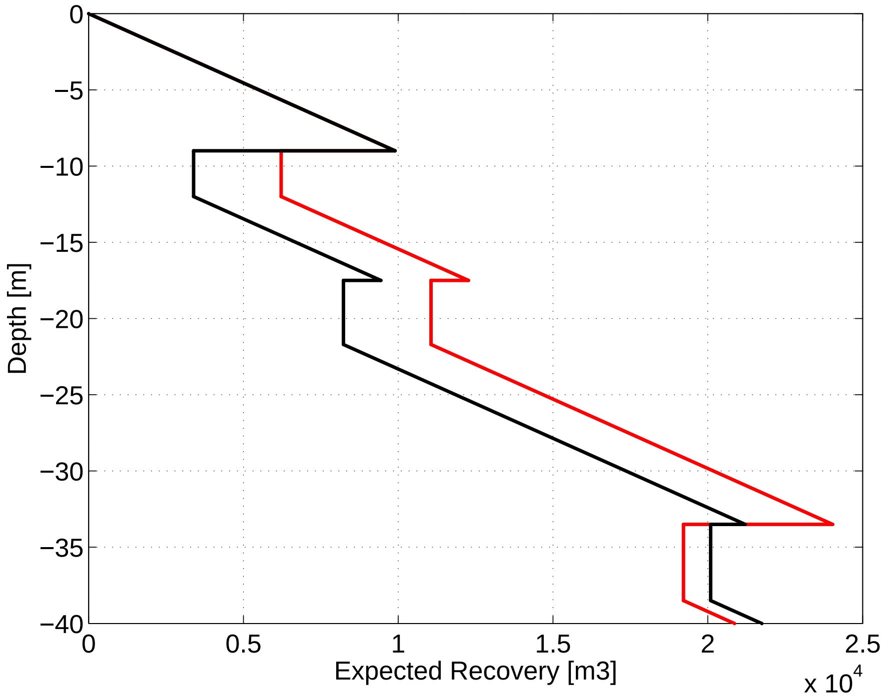

Figure 5: Recovery comparison for different lateral extension of the barriers.

demonstrates a scenario in which the maximum recovery happens at the top of the third barrier in one case while it is maximum at the end of the model for the other case. This explains why the well-placement is mostly crucial to the SAGD drainage process.

In this scenario, the vertical length of the model is $V_m = 40$, and the horizontal length is $H_m = 700$ (*not realistic*). There are three barriers in the reservoir (i.e. $n_b = 3$), with their depth and thickness information listed in table 1. Fig. 5 is generated using EXPECTEDRECOVRY program implemented for this purpose in GSLIB. Details on the calculation of expected recovery had been provided earlier. For the scenario which is plotted in red, the optimal well-placement is at the depth of 34 m while for the scenario in black, the optimal well-placement is at the depth of 40 m. For the general case of statistical recovery evaluation, a program called SIZPOSRECOVERY has been developed in GSLIB to draw samples for H_b and l_c based on the thickness of barriers. The program prompts for the parameter file (shown below). Properties such as the linear regression between thickness and lateral extension (t and H_b) correlation, standard deviation, number of barriers, size of the model and the input file which includes the thicknesses and depths of the barriers can be changed as required. An example of this parameter file is as follows:

This parameter file has been modified for the example of a two-barrier model with the input data file listed in table 2. With the following arrangement, there are cases where the maximum recovery occurs at the top of the second barrier, and some other cases where the bottom of the model is the place for optimal well-placement. The uncertainty regarding the optimal well-placement is the result of limited knowledge which prevents us from determining the length of barrier and its centroid with certainty. Fig. 6 demonstrates the calculated statistically-averaged recovery versus the depth which is give in table 2. As can be seen, the maximum recovery is at the top of the second barrier. That location is chosen as the optimal well-placement. However, this is not the case for all barriers' configuration as shown in

depth.dat	– input Depth data file
1 2	– columns for depth scale, barrier depth
150 15	– model size for hosizontal length, vertical length
2	– number of barriers
recovery.out	– output file
40 10	– slope, interception
30 30	– Standard deviation for every regression fit-barrier

Fig.5 In this work, a one-dimensional Monte Carlo approach is used to evaluate the expected

Table 2: Depth data for case study.

Barrier Depth	Barrier Thickness
4.8	1.7
12.0	1.3

recovery from an oil sands deposit using the SAGD technique. The central parameter to this analysis is the probability of a barrier, which can also be viewed as the statistically-averaged occupancy $< H_b >$ of the model by a barrier. (Such a parameter is needed to determine the "step-backs" in Figure) The parameter $< H_b >$ in turn depends on two random variables, H_b and l_c, which are the lateral size and position of a barrier, respectively. As both these random variables are symmetrically distributed about their mean values, it should perhaps not be surprising that the statistically-averaged occupancy $< H_b >$ is just the mean of H_b, which is given by its linear regression with the barrier thickness t. This was indeed verified by comparing our value m (mean of the Gaussian distribution) to the Monte Carlo result based on 10,000 trials. It should also be noted that the parameter $< H_b >$ is completely independent of the standard deviation of the Gaussian distribution (as expected). It seems therefore pointless to take the Monte Carlo approach in this work. However, in cases where the random variables H_b and l_c are not symmetrically distributed about their means, our Monte Carlo analysis would be ideal.

Future Work

This work has been limited to the uncertainty of the lateral extension of the barriers and their locations based on the data of single-well information. Several other considerations could be applied to analyse the effect on drainage process and optimal well-placement. Properties such as the tortuosity of the barriers could individually be analysed to understand their influence on the overall flow rate and effective permeability. This could greatly affect the recovery assessment and optimal well placement. A small example is provided here to demonstrate that higher tortuosity can considerably lower the vertical permeability

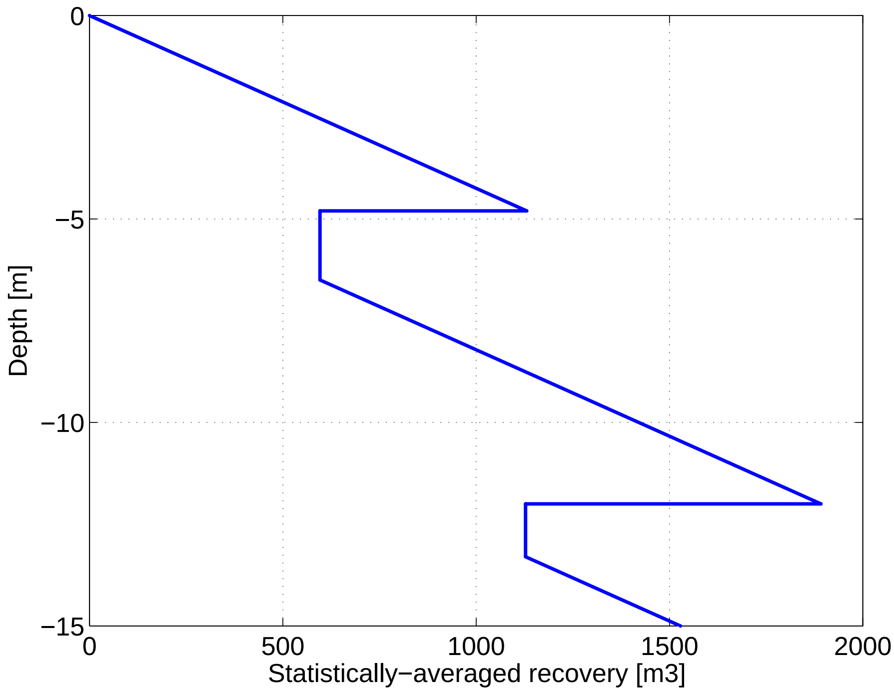

Figure 6: Statistical-averaged recovery vs depth.

and flow rate. Table 3 demonstrates barriers with similar size and thickness, but different tortuosities. The effective vertical permeability ($K_{v\text{eff}}$) of the barrier with higher tortuosity corresponds to much smaller $K_{v\text{eff}}$.

Table 3: Vertical permeability versus tortousity for similar-size objects.

No.	Size	Thickness	Tortuosity Factor	Eff. Kv
1	41235	9.10	1.4164	589.862
2	43211	132930	0.1736	110140

No.	Size	Thickness	Tortuosity Factor	Eff. Kv
1	6708	5.36	1.1926	488.973
2	6707	6.72	0.0557	759.483

In addition to the uncertainty concept, in this paper the analysis is constrained to single-well data. If multiple-data is provided, the correlations between well-data would result in new challenges in optimal well-placement and recovery evaluations.

References

[1] S. Lajevardi, O. Babak, and C. V. Deutsch, "Characterization of geoobjects continuity using moments of inertia," *CCG Report*, no. 13, pp. 128–1,128–13, sept 2011.