Abstract

This paper presents a general history matching technique to create simulation models that honor prior geological information and match production data. The methodology relies on a region-wise perturbation of the probability distributions used to generate the reservoir models. Perturbing probabilities rather than actual petrophysical properties guarantees that the conceptual geologic model is maintained and that border artifacts are avoided. By allowing the properties in different region to be perturbed by different amounts, an efficient match of the observed data can be found. A simple and efficient optimization method is used that can jointly optimize the magnitude of the perturbations and is able to handle a large number of regions. Additionally, the method allows large scale reservoir properties such as the location and regional proportion of facies bodies to be perturbed. The important issue of how to define region geometries is also discussed.

We present a practical implementation of the probability perturbation method within the context of an actual prominent North Sea reservoir by perturbing the local proportion and locations of low-permeability calcite bodies. Results show that a much improved history match can be obtained while maintaining the original geologic concept.

Introduction/Background

Integrating production data into petroleum reservoir models (history matching) is a necessary task of a simulation engineer. History matching is completed with the expectation that the models will have better prediction accuracy than the non-history-matched models. Honoring the conceptual geologic model (CGM) in addition to production data is likely to produce better predictability than models that merely match history. In this paper, the CGM is defined as the geologist’s idea about what is relevant for a particular subsurface and what needs to be captured in the reservoir model. The CGM could be as simple as a variogram model, but could also contain information about the average petrophysical properties, the depositional environment, or the major reservoir structure as well as other geologic aspects. Various geostatistical algorithms exist to build three-dimensional numerical models that depict this geological concept and constrain to reservoir data such as well-log and seismic.

In history matching, a set of measured data, D, is being matched by perturbing a set of model parameters. Finding the set of model parameters is an inverse problem because the measured data does not uniquely define the model parameters. Thus an iterative technique is required to generate a model that matches the production data. Each iteration includes a time-consuming flow simulation, hence the number of iterations needs to be kept to a minimum.

The probability perturbation method (PPM) (Caers, 2003) ensures that the geology is honored in the history-matched realizations and allows those realizations to be found in a reasonably
efficient manner. An initial realization is generated with a geostatistical technique where at each locations, \( u = (x,y,z) \), a conditional probability, \( P(A|B) \), is estimated. \( P(A|B) \) is the probability of the unknown property, \( A \), occurring given other information \( B \). For example, \( A \) could stand for “channel occurs” or “permeability is less than 100 mD,” and \( B \) includes the conceptual geologic model and any hard data values. The gridblock property is assigned by randomly drawing from the probability distribution.

Once the initial realization, \( r^{(0)}(u) \), is generated, flow simulation is run on it and the mismatch with the production data is calculated. To improve the match, Caers proposes to perturb the probability model, \( P(A|B) \) used to generate the initial realizations rather than perturbing the initial realizations directly. This is done by introducing another probability model, \( P(A|D) \), that depends on the production data, \( D \). The perturbations of \( P(A|B) \) by \( P(A|D) \) is achieved by combining both conditional probabilities into a new probability model, \( P(A|B,D) \) that is used to populate the next realization. The method proposed by Journel (2002) is used to combine such probabilities. \( P(A|D) \) is defined with a single perturbation parameter, \( r_D \), as follows:

\[
P(A|D) = (1-r_D)r^{(0)}(u) + r_DP(A) \in [0,1] \tag{1}
\]

where \( P(A) \) is the marginal distribution (probability that \( A \) occurs regardless of the other data), and \( r_D \) varies between \([0,1]\) and controls how much the model is perturbed.

To better understand the relationship between \( r_D \) and \( P(A|D) \) consider the two limiting cases when \( r_D=1 \) and \( r_D=0 \). When \( r_D=0 \), \( P(A|D) = r^{(0)}(u) \) and via Journel’s method, \( P(A|B,D) = r^{(0)}(u) \); hence, the initial realization is retained in its entirety. When \( r_D=1 \), \( P(A|D) = P(A) \); therefore, \( P(A|B,D) = P(A|B) \), and if the random seed is changed, a new realization, \( r^{(1)}(u) \), is generated that is as equally probable as \( r^{(0)}(u) \). The parameter \( r_D \), therefore, defines a perturbation of an initial realization to another equiprobable realization (Caers, 2003).

There may exist a value of \( r_D \), for which the perturbed reservoir model matches the production data better than the initial realization. Finding the optimum realization, is a problem parameterized by only one free parameter, \( r_D \); therefore, finding the optimum realization is equivalent to finding the optimum \( r_D \) value.

\[
r_{D_{opt}} = \min_{r_D} \{ O(r_D) = \| D^S(r_D) - D \| \} \tag{2}
\]

where \( O(r_D) \) is the objective function, which is defined as some measure of difference between the simulated production data \( D^S(r_D) \) and the observed field data, \( D \). The value of \( r_{D_{opt}} \) and consequently the optimum realization, \( r_{D_{opt}}^{(1)}(u) \), can be selected using any simple one-dimensional optimization routine.

When using a 1D search to find the best realization (best \( r_D \)) between two equiprobable realizations (\( r_D=0 \) and \( r_D=1 \)), one does not expect to find an acceptable overall match to the production data. Thus, a two-loop optimization routine is necessary where the previous optimum realization is used as the initial realization in the next step, replacing \( r^{(0)}(u) \) in Eq. (1). This constitutes the outer loop of iteration that will be stopped when a satisfactory history match is achieved. Also during each outer iteration, the random seed is changed. By doing so, a new equiprobable realization is generated when \( r_D=1 \). This allows the method to again search between two equiprobable realizations in the next inner iteration.

This method is theoretically well-founded (Caers, 2004), and it works well with a small amount of wells and when the geological variability is relatively constant over the reservoir domain. In actual reservoirs the amount of wells may be large and the geology (e.g. average petrophysical properties or proportion of facies) may be strongly varying. This paper proposes some essential modifications to the PPM and provides an application to an actual reservoir.
Development for Practical Applications

Going from theory to practice is a non-trivial step, and a number of specific issues arise that need to be addressed. In general, these issues can be summarized as follows:

1. Identifying which model parameters to modify and the range of perturbation for those parameters while ensuring that the modifications are done in a geologically consistent manner.
2. Defining how to make different changes for different parts of the reservoir model (which is often necessary to achieve a match) while maintaining the efficiency of the method.

Model Parameters

Determining which parameters in history matching to change is a difficult task since a large number of parameters affect production data, and all or at least most of the parameters have some amount of uncertainty associated with them. To make the procedure efficient, parameters that have the most significant impact on the production need to be perturbed.

For example, Figure 1 shows the influence of two different parameters on water production. For the parameter on the left, there is a relatively small impact on production for its range of uncertainty; conversely, the parameter on the right has a significant impact when varied. By perturbing the parameter on the right, the water rate for this well will likely be matched; however, perturbing the parameter on the left will never result in a history match no matter how many iterations are completed.

Part of defining the CGM consists of deciding which parameters to freeze and which parameters to modify (within their range of uncertainty). In some cases, parameters such as gridblock permeability or porosity, aquifer strength, and relative permeability will have enough impact on production data to match the observed reservoir data. In other cases, large scale parameters such as reservoir structure, fault properties, or facies distribution will have to be perturbed for a match to occur. Nevertheless, an algorithm to perturb these large scale parameters in a practical and geologically consistent manner is largely lacking.

Figure 1: Sensitivity of two parameters and their affect on production data.
Reservoir Regions

The probability perturbation method (PPM) is able to perturb large scale parameters and honor the conceptual geologic model; however, for reservoirs with vastly different properties in different parts of the reservoir, the efficiency of the PPM is not satisfactory. For many history matching applications, the reservoir models need to be able to account for spatial variability by perturbing parameters by different amounts in different regions of the model (Hoffman and Caers, 2003). The region definition is left to the user, and while they may have any arbitrary shape, they may not overlap. The reservoir regions be denoted as \{R_1, R_2, \ldots, R_K\} where K is the total number of regions, and the entire realization is \( R = (R_1 \cup R_2 \cup \ldots R_K) \). P(A|D) is defined for the entire reservoir, R, but its local value depends on the region definition: when \( u \) is located in region \( R_k \), the perturbation parameter takes on a value of \( r_{Dk} \). Therefore P(A|D) can have different values for different regions of the reservoir, and the following equation for P(A|D) is used.

\[
P(A|D) = (1-r_{Dk})f^{(0)}(u) + r_{Dk}P(A)
\]

Each perturbation parameter is updated based on how well the simulated production in a region matches the observed production data from that region. If the match is good, \( r_{Dk} \) is reduced, and if the match is poor, \( r_{Dk} \) is increased. Figure 2 shows an illustrative 2D example about how this works.

![Figure 2: Perturbing two regions by separate amounts.](image)

There are three wells, one injector in the middle and two producers. In the initial model, the production well on the right (Region 2) is matching its production data quite well, whereas the well on the left (Region 1) is not matching nearly as well. Therefore, Region 2 will require a small perturbation parameter value, and Region 1 will require a larger perturbation. In the perturbed model, Region 2 is changed only slightly; the location of the bodies is the same, and their shapes have changed somewhat. Conversely, the bodies in Region 1 are considerably different in the perturbed model compared to the initial model.

Notice there are no model artifacts or discontinuities along the region border illustrating that the geology is always maintained. The reason for not creating artifact discontinuities can be explained by the nature of the sequential simulation algorithm and by the perturbation method applied. In sequential simulation, each grid block is simulated based on any reservoir data and on any previously simulated grid block properties. The method searches for any such previously
simulated grid locations in an elliptical search neighborhood. This search neighborhood may (and should) cross the region-boundaries. When simulating a grid block in one region, the grid block properties in other regions are used to determine \( P(A|B,D) \), hence creating continuity across the boundaries. Secondly, geological continuity is assured in the perturbation method through the probability \( P(A|B) \), which is not calculated per region but for all regions together (Hoffman and Caers, 2003).

By using the regional PPM, facies bodies are merely moved around, but a situation may occur where the amount of bodies in one region will be different than the other regions. In this situation not only the location of the bodies but also their regional proportions (RP) need to be perturbed. To make a joint optimization of \( r_{Dk} \) (defining the position of bodies) and \( RP_k \) efficient, a coupled optimization is developed as follows:

\[
RP_k^{NEW} = RP_k^{OLD} + i_k \cdot (r_{Dk}) \cdot Fc \quad \text{for } k = 1, ..., K
\]

where \( k \) is the region indicator and \( K \) is the total number of regions. \( Fc \) is a user-defined constant that characterizes the amount of change allowed each step. Since the values of \( r_{Dk} \) range from 0 to 1, when \( r_{Dk} \) equals 1, \( RP_k^{OLD} \) is either increased or decreased by an amount equal to \( Fc \). The indicator term, \( i_k \), determines whether the LP should increase or decrease and is defined as follows:

\[
i_k = \begin{cases} 
1 & \text{if increase in regional proportion is desired} \\
-1 & \text{if decrease in regional proportion is desired} 
\end{cases} \quad \text{for } k = 1, ..., K.
\]

**Case Study**

The case study is a prominent North Sea reservoir with 22 wells (14 producers and 8 injectors) and 5 ½ years of production data. There are four major horizons and the top horizon is isolated from the lower three horizons by an impermeable shale layer. There is a gas cap and a weak aquifer present in the reservoir. There are a number of faults in the reservoir, but some communication between the fault blocks occurs because none of the faults are completely sealing. A significant number of very low permeability nodules are found in the reservoir. They were created by the diagenesis of calcite and tend to have a lenticular shape. They typically have an areal extent of a few meters to tens of meters. Where clusters of these bodies are found, they can have a large affect on fluid flow in the reservoir.

**Simulation Model**

The reservoir model is a structured stratigraphic model with 39 cells in the x-direction, 98 cells in the y-direction, and 41 cells in the z-direction, but only about half of those cells are active. There are just over 70,000 total active gridblocks in the model. The porosity is mapped using a kriging algorithm, and the permeability is calculated from the porosity using a linear transform. There are 17 separate relative permeability regions in the reservoir, and the various curves are calculated from Corey type curves with different end points and/or exponential coefficients. The calcite bodies are relatively thin, so they are given no vertical thickness in the simulation model. Gridblock containing a body or a cluster of bodies will get a reduced or zero z-direction transmissibility. For this case, the regional proportion (RP) is not a volumetric value of proportion, but rather the proportion of gridblocks that have a reduced vertical permeability due to the presence of the calcite bodies. For example if the RP is 30%, this does not mean that 30% of a region’s volume is calcite, instead, 30% of the gridblocks in the region have reduced vertical permeability.
The location and proportion of calcite bodies is uncertain, so they must be stochastically built into the reservoir model. The concept of multiple-point geostatistics and the SNESIM algorithm (Strebelle, 2000) are used to model the bodies. SNESIM relies on a training image to infer the geologic properties being modeled. A training image is a non-conditional and purely conceptual depiction of the geological patterns deemed relevant for a particular subsurface. The training image used for the current work only needs to be 2D because these bodies are modeled with no z dimension. Little information is known about the bodies’ shape and distribution; therefore, the bodies are randomly dispersed. Although the size and shape of the bodies is not precisely understood, we assume that where clusters of bodies occur, their affect is over a minimum area of 0.04 km². On average the gridblocks have a length around 100 m in the x and y directions, so the size of the bodies in the training image is typically two gridblocks square.

To perform history matching with the probability perturbation method, a method for defining regions in the reservoir is required. Streamlines are well suited for the job because they directly show the flow paths by which fluid enters a production well (Milliken et. al., 2001). These paths identify the gridblocks that, if changed, will have an obvious impact on a well’s production. All blocks hit by the set of streamlines entering a well define the “drainage zone” for that well. The various drainage zones define the geometry of the regions used for history matching in this case study.

Water, oil and gas rates for the 14 production wells and RFT pressure data from a number of both injector and producer wells is available; however only water rate and RFT pressure are used in the objective function. In the simulation model, wells have fixed liquid rates; hence, if water rates are correct, oil rates are also correct as well as the water cuts. The rates are matched using monthly averages. The objective function is simply defined as the square difference between the simulated production and measured production data. Depending on the well there is about 17-44 months of production for each well. Equal weight is given to each data point, not to each well, hence a well that is producing for 40 months will have twice the influence of one that has been producing only 20 months. Likewise, a well with RFT measurements taken over 200 m will have twice the influence as a well where only 100 m were measured.

Parameters such as permeability/porosity, relative permeability and fault transmissibility were examined to determine if they should be perturbed in the history-matching algorithm. However, it was determined that the overriding factor in the model is the presence of calcite bodies. The calcite bodies are perturbed using the regional probability perturbation method. Both the locations and the regional proportions of the bodies are allowed to vary. The bodies are included in the simulation layers 11-36 of the 41 total layers.

Results

By perturbing only the calcite bodies and allowing all the other parameters to be the same as the initial model, a quality history match is achieved for both the rates and the pressures. The water rates for three wells are displayed in Figure 3, and the RFT pressure measurements for three different wells are shown in Figure 4. The black data (lines and dots) is the observed data, and the light gray data is the history matched results. The line with the crosses represents the water rate data from the initial model, and the open diamonds are the initial pressure data.

For well P-3, the initial model has a water rate and breakthrough time that is much too high and much too early compared to the observed data. The history matched breakthrough time is very close and the rate is improved significantly. For well P-4, water is breaking through too late in the initial model, but in the history matched model, the data is matching much better. Wells P-3 and P-4 have the largest mismatches and thus show the greatest improvements, but
other wells also improved. The initial matches were closer, but they still showed some improvement (e.g. Well P-10).

The pressure match was also improved. For some wells such as P-13, the pressure match from the initial model was already quite good, and that remained so in the history-matched model. Other wells such as I-6 went from a poor match to a very good match, and while well I-5 showed some improvement.

Figure 5 shows the locations of the calcite bodies for two layers in a small segment of the reservoir. The proportion of bodies in the history matched model ranges from 1 % to 53 % with most regions having between 10 % and 20 %. The region with 53 % of its gridblocks affected by calcite bodies corresponds to well P-3. This well showed water breakthrough 2 years too early in the initial model, hence requiring a significant proportion of bodies to impede water flow.
Conclusions

The practical application of the probability perturbation method (PPM) to a real complex North Sea reservoir is presented. The method can efficiently match production data including both RFT pressure and water rate data to the observed data quite well. The prior geologic concept of the reservoir is maintained in the simulation model; in particular, calcite bodies that have low vertical transmissibility were stochastically modeled. The locations and regional proportion of the bodies is highly uncertain, and these parameters were allowed to be perturbed in the history matching process. More generally this work shows that large-scale structures such as facies bodies can be perturbed to achieve a quality history match.

References


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