Updating Stochastic Reservoir Models With New Production Data
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Abstract
In current practice history matching is often performed on upscaled reservoir models without updating the original geological model. Taking into account new production data in an existing model is often problematic because of the lack of appropriate techniques. This problem becomes crucial when using geostatistical models. In such a case, the integration of new static and dynamic constraints requires the modification of an initial realization without destroying the initial history match and the overall geostatistical properties.

This paper presents a new methodology based on advanced history matching techniques for updating dynamically 3D stochastic reservoir models to account for new production data. The proposed approach is based on the gradual deformation method. It allows local or global smooth transformations of the model while conserving the overall statistical characteristics. History matching is performed by coupling this method with an optimization process which integrates geostatistical modeling, upsampling, and fluid flow simulation in the same loop. This approach provides great flexibility in history matching various types of production data. In addition, inversion parameters can be selected throughout the entire modeling loop, from the facies spatial distribution, to petrochemical parameters and fluid flow parameters. Finally, local transformations may be performed to account for new wells or to update the reservoir model with new dynamic information.

A successful application to a 3D stochastic reservoir model inspired from a real field is presented. The first step was to perform a history match using the production history available from an initial group of production wells. Then, new dynamic information is acquired from infill wells and over one year of additional production data. The heterogeneity distribution is locally modified by gradual deformation to update the model with this new information. The benefit of the proposed approach for improving the model characterization and reducing uncertainty on production forecasts is demonstrated.

Introduction
In its most basic form, traditional history matching consisted of modifying the input parameters of the flow simulator and visually comparing production curves with real production data. The process continues until an “eyeball” match is obtained. Typically, automatic, or assisted history matching (AHM) is performed in a very similar manner to the traditional approach. The AHM approach is to formulate the history matching problem as a minimization problem, where the objective function to be minimized is usually the squared difference of the simulated data values and the corresponding real production data (see [1], for example). The optimization routine evaluates the objective function, selects new input parameters, replaces them in the flow simulator input file, and reruns the simulation in order to re-evaluate the objective function. When the objective function has reached a low-enough value, or when a certain number of flow simulations has been performed, the procedure stops. Recent publications [2-5] have shown that using this procedure, very good history matches can be obtained.

However, a very fundamental problem arises when we consider that many reservoir flow models have been upscaled from very complicated, fine-grid stochastic models. Thus, when the flow model has been modified by AHM, the fine-grid and the coarse-grid models no longer correspond. One may argue that this may not be important, since we will always continue to use the coarse-grid model for reservoir predictions and production forecasts. However, this neglects the possibility that after the history match new wells may be drilled and produced. The fine-grid geologic model can easily be updated with new static well data, but it is not clear how to update the coarse-grid model, considering that it is no longer consistent with the fine-grid model. How can one modify the already history-matched coarse-grid model with this new data without destroying the previous match?

In this paper, we will advocate a different approach to AHM that includes in the history-matching procedure not only the coarse-grid model and flow simulation, but the entire geomodeling workflow. By including the entire modeling and simulation workflow, the fine-grid model can be updated in a consistent manner that avoids the problem described above. In addition, including the geological modeling workflow within the AHM procedure brings many advantages when analyzing uncertainty. We will explore this idea further in the discussion. In the body of this paper, we will principally focus...
on the problem of how to update the geologic model with new static and dynamic well data. This will be done using a simple synthetic case based upon a real reservoir.

In the past, incorporating the entire modeling workflow has often been difficult to implement - modifying the fine-grid during the history matching process can potentially mean modifying the values of many millions of grid blocks. In addition, modifying geologic models cannot be done in any manner - the modified model must remain consistent with the input of the geologist. In particular, stochastic properties such as spatial correlations must be preserved. Finally, for the case of infill wells, we must be able to modify only sections of the fine-grid model, while leaving other parts untouched. The gradual deformation method allows us to fulfill these conditions.

**Gradual deformation method**

The gradual deformation method has been described by Roggero and Hu [6], and thus will not be described in great detail here. Essentially, the gradual deformation method simply parameterizes a stochastic model such that it can be modified in a continuous, gradual manner while maintaining the stochastic properties of the model. The gradual deformation method can be applied to Gaussian-based stochastic models, generalized sequential-simulation techniques [7], and even object-based models [8-9]. In this paper, we will be generating Gaussian realizations of porosity and permeability for our geologic model. In this case, the gradual deformation method uses a very simple equation that combines two or more equiprobable, unconditional Gaussian realizations using a small number of parameters to gradually and continuously modify a Gaussian stochastic realization. Equation 1 shows the equation for combining two images, \( Z_1 \) and \( Z_2 \), to obtain another image \( Z \).

\[
Z(\rho) = Z_1 \cos(\rho \pi) + Z_2 \sin(\rho \pi)
\]  

(1)

In this case, a single gradual deformation parameter \( \rho \) is needed to modify the \( Z \). Note that if \( \rho = 0 \), \( Z = Z_1 \). If \( \rho = 0.5 \), \( Z = Z_2 \). One can thus imagine how the gradual deformation method works with AHM. Two or more independent, equiprobable, Gaussian realizations are created, and the AHM algorithm modifies the gradual deformation parameter(s) in an attempt to improve the match.

Another feature of the gradual deformation method is its ability to chain together optimizations by taking the best image \( Z \) of a previous optimization and combine it with another independent image. This sequential optimization is drawn schematically in Figure 1. An initial optimization modifies \( \rho \) until an optimal realization \( Z_3 \) is found. In Equation 1 we replace \( Z_1 \) by \( Z_3 \), and a new independent image replaces \( Z_2 \). A new optimization then proceeds with the initial value of \( \rho = 0 \) (thus starting the new optimization at the previous, optimal realization \( Z_3 \)).

A very significant improvement of the gradual deformation method was described by Le Ravalec *et al*. [10]. These authors showed that if the combined stochastic realizations were independent, unconditional realizations of Gaussian white noise (i.e. uncorrelated Gaussian realizations drawn from a normal distribution), then one can apply the gradual deformation method on only part of the stochastic realizations and still maintain the stochastic properties of the resulting image. Le Ravalec *et al*. used the FFT-MA algorithm [11] for adding a variogram structure to the final, combined Gaussian white noise realization (\( Z \)). Hu [7] showed that this approach can work for any sequential simulation algorithm. In this work, we will use the FFT-MA algorithm, and describe in more detail by using the synthetic example how local gradual deformation can be applied.

**Synthetic Example**

We demonstrate our integrated approach by using a test case derived from the PUNQ-S3 problem [12] which is based upon a real west African field. The PUNQ-S3 model is used quite often for history matching and uncertainty analysis studies. The reservoir model consists of a 19x28x5 grid with 1761 active cells. Although the number of active cells is small with no upsampling, this does not imply that our approach is limited to small reservoir models. See Feraille *et al*. [13] for the application of this approach to a real field case. A real case history matching example Any upscaling algorithm can be integrated quite naturally into the workflow to go from the geological model to the flow model. Figure 2 shows a map view of the reservoir color-coded by the top surface depth. Strong aquifer support comes from the north and west of the field. To the east and south, two faults close the reservoir. The petrophysical properties were recreated using input parameters consistent with the original PUNQ-S3 model. 6 wells (PRO-1, PRO-4, PRO-5, PRO-11, PRO-12, and PRO-15) are initially on production. Then, after approximately 3000 days, two more wells, X1, and X2, are drilled and produced for over two years. The location of these wells can be seen in Figure 2.
The modeling workflow. The entire modeling workflow is shown in Figure 3. For each of the 5 layers, a vector of Gaussian white noise of length 19x28, is generated ("Generate" components). This vector is passed to the FFTSim component, which converts it into an image of correlated Gaussian field using the FFT-MA algorithm and a variogram that is different for each of the 5 layers. Then, for each layer, the realization is subsequently transformed to a non-standard mean and variance, and conditioned to the porosity values at all the wells. At this point, the porosity realizations are grouped together within the GeoModel component. Here, the permeability fields are generated using a porosity/permeability relationship for each layer, and the vertical permeability is then generated using a Kv/Kh relationship for each layer. The resulting realizations are sent to the flow simulator (ATHOS, in this case). Note that although not present here, an upscaling component can easily be inserted into the workflow between the GeoModel component and the flow simulation.

The reference case. The historical production data (shown in Figure 4) were created by flow simulation on a reference image. The water cut, bottom-hole pressure (BHP) and gas-oil ratio (GOR) were recorded in order to be used during the history match. Figure 5 shows the reference image for the bottom layer 5. Note that the axes of the stochastic realization are rotated with respect to Figure 2, and that the entire porosity field is shown and not only the active grid blocks. The reference images and historical production data were generated using the same workflow as shown in Figure 3. The geostatistical parameters of the geological model are defined in Table 1 and Table 2. Note that the correlation lengths, angles and anisotropy ratios are the same for porosity and permeability.

For the history match, we are going to assume that we know perfectly all the variograms, means, variances, porosity/permeability relationships, and Kv/Kh relationships for all the layers. Thus, we will simply “forget” the reference image by changing the seed values of the Gaussian white noise generators, and then subsequently try to history match the production data by applying the gradual deformation method on all 5 layers. All the uncertainty in the production data is thus due to errors in the stochastically-generated realizations. Clearly, in a history matching case of a real field, we will not have perfect knowledge of the geologic parameters. This is done simply for illustration purposes - for more complex cases with much greater uncertainty, the approach remains the same. For example, the means and variances of the porosity for each layer, as well as the parameters within the variogram may be considered for history matching. The Kv/Kh ratios and the phi/K correlations may be considered as well (see [13]).

Initial history match. A history match was performed on the 6 wells over the first production period. The objective function was reduced to below 10% of its original value (see Feraille et al. [13] for details on the construction of the objective function). This match was done using global gradual deformation of the entire 19x28 realization of Gaussian white noise for each layer, combining 4 independent realizations for each layer (3 deformation parameters per layer, 15 parameters in total). The history matches of the BHP (not shown) were excellent. The matches for the GOR and the water cut are shown in Figure 6 and Figure 7 respectively. The matches of
production are in general quite good. However, some differences can be observed for certain wells. The BHP was matched very well, followed by decreasing accuracy in the GOR and water cut. The simulation results are quite dependent on the particular stochastic image. This can be seen by comparing the reference and history matched stochastic realizations of layer 5 in Figure 5 and Figure 8. A better history match could be obtained by continuing the optimization procedure, or by increasing the number of realizations that are combined. For this case we simply halted the optimization process at this point due to time considerations.

It is important to note that in the history matching procedure we are in fact simply modifying the Gaussian white noise images of all 5 layers, and not directly the values of porosity and permeability. At the end of the history match, the optimal Gaussian white images are saved. This is important when we proceed to updating the model with new data.

**Updating the stochastic model – static data.** We have judged that our previous history match was reasonable. As a consequence, we then “drill” wells X1 and X2 and subsequently produce for over two years. The previously matched stochastic realizations were modified by the static conditioning data of X1 and X2. Layer 5 updated with new static data (but not dynamic data) is shown in Figure 9. This image differs slightly from the previous, history-matched image in Figure 8. Note that if added wells are within the correlation length of previously drilled wells, conditioning a matched model to new data can have positive or adverse effects on the history match. In this case for example, the matches for the water cut for wells PRO-12 and PRO-1 were adversely affected. The history match of most other wells was impacted as well, but to a lesser degree. Again, the BHP was matched very well, followed by decreasing accuracy in the GOR and water cut. The simulation of well X1 showed a very accurate match without history matching, even with the GOR varying significantly (not shown). This is unfortunately not the case for well X2. The water cut showed early breakthrough on the simulation while the historical data had only a negligible amount of breakthrough at the end of the historical period (Figure 10). Figure 14 shows the water cut curves for wells X2, PRO-11, PRO-12, and PRO-4.

**Updating the stochastic model – dynamic data.** At this point, we would like to modify the stochastic image to improve the match of the water cut at X2, while at the same time not perturb the good history match of other wells such as X1, PRO-4 or PRO-11. This was done using local gradual deformation. A 13x15 zone in layer 5 was defined within the 19x28 grid as shown in Figure 11, which includes the well X2, but none of the other producing wells. Note that the local gradual deformation method does not require a square-shaped zone. Layer 5 and the location of the zone were selected with the knowledge that the water breakthrough was most likely coming from the aquifer to the west and north, following the permeability heterogeneity trend. Starting with the best image of Gaussian white noise from the previous history match, the subset of Gaussian white noise representing the zone is combined with two independent realizations of Gaussian white noise in an attempt to improve the water cut in well X2. Figure 12 indicates the initial porosity image of layer 5 before the history match. Figure 13 shows the final porosity image of layer 5 after the history match. Note that far from the zone the realization has not been modified. Note as well that that variogram structure is preserved across the frontier of the zone. This can be verified visually that no artifact of the modification is created along the border of the zone (Figure 13).

The water cut production curves are given in Figure 15. In addition to well X2, we show the water cut curves for wells PRO-11, PRO-12, and PRO-4. We can compare these curves to the water cut values before local gradual deformation (Figure 14). The simulated water breakthrough in well X2 is much closer to the historical data. The local gradual deformation had no impact on the match of wells PRO-4 and PRO-11. However, there is an impact on well PRO-12. The reason for this is that modifications within a zone will have an impact upon a border region surrounding the zone. The size and shape of this border region depends very highly upon the spatial correlation and direction.

**Discussion**

Using a simplified synthetic example, we have shown how the gradual deformation method can modify zones within a stochastic realization by modifying the underlying realization of Gaussian white noise. However, as was noted above, modifications are not always limited to within the zone. For reservoir features such as channel bodies that may have very high correlation lengths, modification of the channel body in a zone may modify the channel body location everywhere. When the correlation length is small, then small or negligible modification of the stochastic realization may occur outside the zone. These aspects must be considered when selecting zones for local gradual deformation.

In addition, zones must also be selected intelligently with consideration to potential flow paths. In the example above, we suspected that the water breakthrough was coming from the aquifer to the west and north, and thus selected the zone accordingly. In many cases though it may not be immediately clear how to best select a zone. Future work will involve the selection of zones using streamlines, which seem a natural way to identify influential regions for production wells [15].

We have emphasized the gradual deformation method for modifying stochastic realizations globally and locally within zones. The pilot point method [14] is another popular parameterization method that also can modify locally stochastic realizations. However, if not used carefully, the pilot point method can modify the stochastic realization that is not consistent with the prior geostatistical properties. In addition, the pilot point method can only modify stochastic pixel-based images, whereas the gradual deformation method has been extended to object-based algorithms as well [8-9].

In the synthetic example above we concentrated on uncertainty in production forecasts due to the stochastic realization. In other cases, the stochastic image may not be the greatest source of uncertainty. Uncertainty in the fault transmissibilities, or the mean values of porosity and permeability for example might be predominant, and the uncertainty in the stochastic image may be insignificant. In this case, the gradual deformation method will not help in significantly improving the history match. However, this does
not imply that history matching should then be performed on the upscaled, coarse-grid flow simulation model. If, for example, the mean porosity for unknown for all 5 layers in the synthetic PUNQ-S3 case above, only by incorporating the entire workflow such as shown in Figure 3 within the AHM procedure can one consistently treat all uncertainties. In addition, when performing uncertainty analysis such as when using experimental design [16], only by combining the entire workflow can one properly analyze the impact of uncertainty of all the parameters within the workflow. For example, if the uncertainty analysis is performed only on parameters in the flow simulator, then it will not be possible to analyze the uncertainty of the top depth structure or fault location.

Conclusions

Standard assisted history matching techniques modify only the parameters that are available within the upscaled, reservoir flow model. This approach has many difficulties. The main problem that we emphasized in this paper is the updating of the matched model with new well data. Another important difficulty is the analysis of uncertainty throughout the entire modeling process, from generation of the geologic model to upscaling and flow simulation. Uncertainty analysis on only the matched model with new well data. Another important difficulty is the analysis of uncertainty throughout the entire modeling process, from generation of the geologic model to upscaling and flow simulation. Uncertainty analysis on only part of the workflow ignores other potentially significant sources of uncertainty. A better approach is to incorporate the entire modeling workflow within the assisted history matching framework. Moreover, efficient and intelligent modification of stochastic realizations by history matching requires advanced modeling techniques. We propose the gradual deformation method to perform this task. The method allows the local or global modification of the stochastic model while at the same time preserving the statistical and stochastic parameters of the model.

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Reference

Table 1. Reference case porosity parameters

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<th>Standard deviation</th>
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<tr>
<td>Angle</td>
<td>-60</td>
<td>-60</td>
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</table>

Figure 4: The historical production data for the synthetic PUNQ-S3 case. For all the wells, a constant oil rate of 150m3/day is specified, with a minimum BHP of 120 bars. As seen on the left, several wells reach the minimum BHP during the production period. The middle graph shows the GOR. Several wells produce free gas. On the right, the water cut curves indicate varying degrees of water breakthrough at the wells.
Figure 5: The reference porosity image for layer 5. Note that the axes are the inverse of the axes shown in Figure 2. In addition, all the grid blocks in the stochastic simulation are shown, and not only the active grid blocks.

Figure 6: Initial history match of the GOR. The main features of the GOR curves are well reproduced.

Figure 7: Initial history match of the water cut. For wells PRO-11 and PRO-12, the match is quite satisfactory. On the other hand, the match is marginal for wells PRO-15 and PRO-5.

Figure 8: Porosity of layer 5 after initial history match on 6 production wells. The blank grid block near the center-top are values above 0.4.
Figure 9: Porosity of layer 5 of initial history matched model but newly conditioned to static data from wells X1 and X2. Note that this image differs slightly from Figure 8.

Figure 10: Comparison of the water cut for well X2 between the historical data and the simulation using the initial history matched model conditioned to the new well data. The simulation overestimates the water cut.

Figure 11: The selected zone to be modified to improve the water cut history match for well X2.
Figure 12: Porosity of layer 5 before history matching using local gradual deformation.

Figure 13: Porosity of layer 5 at the end of the history match using a single zone. Note that far from the zone the porosity realization is unmodified.
Figure 14: The water cut curves for wells PRO-11, PRO-12, PRO-4, and X2 before updating the stochastic image using local gradual deformation.

Figure 15: The water cut curves for wells PRO-11, PRO-12, PRO-4, and X2 after the history match using local gradual deformation. Note that the water cut curve for X2 has greatly improved with respect to Figure 14. Note as well that the curves for PRO-11 and PRO-4 are unchanged. However, the curve for PRO-12 has been modified.