History Matching by Integrating Regional Multi-Property Image Perturbation Methods with a Multivariate Sensitivity Analysis

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ABSTRACT

Reliable reservoir characterization is essential to predict future behavior, however, scarcity of data results in uncertainties and consequently, high variability in simulated data. This variability can be decreased by history matching where uncertain parameters of the reservoir are altered to minimize the mismatch between history and simulated data. The most complex uncertain parameters to be treated are characterization of petrophysical properties. Changing petrophysical properties is still a challenge due to the characteristics of the parameter. To reduce uncertainties in the spatial distribution of petrophysical properties, we can use image perturbation methods to redefine the probability distribution function for each property. Previous works present different approaches to perturb a single property of the reservoir, this paper moves further and we present a methodology to simultaneously treat multiple petrophysical properties. These properties can be categorical (facies) or continuous (porosity and permeability) and, together with a multivariate sensitivity analysis, we can identify which regions and attributes affect the mismatched objective function and so reduce the subjectivity in perturbing the model. To test our methodology, we use case study UNISIM-I-H, a complex synthetic reservoir with 25 wells and 11 years of history data. This approach has shown to be efficient and to allow for local

perturbations, making possible the match of individual wells without mismatching others. Our methodology guarantees consistency of the matched reservoir model by preserving well log data, variograms and the relationship between different properties. Finally, this work contributes to the area of history matching by facilitating the integration of the process under a framework that takes into account probabilistic approaches and geostatistical modeling.

Keywords: Image perturbation, geostatistical modelling, history matching, regional perturbation, sensitivity analysis

1. INTRODUCTION

Good reservoir characterization is essential to an exploitation strategy, risk analysis and production forecast. The high uncertainty in reservoir characterization is due to the difficulty to describe complex geological structures based on minimal production and well data.

Therefore, a single “best” history matched model is no longer a goal, since it provides limited value in terms of uncertainty in a forecast. To quantify uncertainty, a probabilistic history matching with multiple models that honor the history data is now preferable. Using multiple models allows us to define the probability of forecast production, bounded by a confidence interval. Having multiple forecast scenarios increases the likelihood that the true solution is within the uncertainty bounds.

Different reservoir properties, e.g. facies, porosity, net-to-gross ratio and permeability, have different impacts in reservoir production. This influence must be measured and, if necessary, the uncertainty reduced for that property.

The process of reservoir modelling consists of two stages: reservoir models are generated with all available static information (e.g. well log, seismic data, core and

geology) and, because they rarely match the history data, they are altered until the output matches the history data (**Hoffman and Caers, 2007**), which means the existent misfit is acceptable for the engineer.

In traditional history matching, reservoir images were treated using multipliers in geostatistical parameters to improve well behavior, minimizing the misfit between production data and history data (**Mattax and Dalton 1990; Miliken et al., 2001**). This method can achieve good matches but in doing so destroys any geologic knowledge, as well as well data and continuity over the reservoir, creating a model without structural consistency.

History matching with multiple uncertain parameters needs extreme effort and has no guarantee that a good history matching will give good forecast. History matching is an inverse problem, which means there are multiple answers to match the data. **Tavassoli et.al (2005)** showed that only with 3 uncertain parameters on a simple synthetic case there were several answers for the same history data, although they gave different forecast in long term.

Consequently, even if the model reproduces history data correctly, it will probably provide unreliable forecasts over time.

Other methods have been used to perturb the reservoir while preserving its geological structure. Inspired by **Journel (2002)**, who combines different types of information, **Hoffman (2005)** suggested a method to perturb large-scale properties (e.g. facies) while honoring the geologic concept. The algorithm starts from a prior distribution $P(A/B)$, that is the probability of an unknown grid block property A occurring given some static information B , and perturbs it (the initial probability) by introducing a new probability $P(A/D)$. This is the probability of the event occurring given the production data D . The two probabilities are combined, assuming independence

between them and a new probability is created $P(A/B, D)$. This method can be applied globally or regionally.

Several cases have already been studied using the Probability Perturbation Method (PPM). **Hoffman and Caers (2003, 2005)** presented several applications for the method: in the characterization of high permeability channels, fractured reservoirs and a synthetic 3D fluvial channel model based on a North Sea reservoir. In every case the methodology showed promising results, with faster convergence and better matched models in regional perturbation than in global perturbation.

For continuous properties (e.g. porosity, permeability etc.), **Mata-Lima (2007, 2008)** suggested the use of Co-Simulation to change the probability distribution function of the conditioned property. Co-Simulation can be applied when two variables are spatially dependent. If the primary and secondary variables describe the same property, Co-Simulation may be used to reproduce a spatial pattern from the secondary variable. The method is easy to implement and only needs two inputs: the variogram from the primary variable and a correlation coefficient. The bigger the correlation coefficient, the more the spatial pattern is preserved and less flexibility is given to the following iteration.

Oliveira (2014) used this methodology to do history matching on a complex case study with 25 wells, and 11 years of history data (production rates and bottom-hole pressure - BHP). Like PPM, Co-Simulation can be used globally or regionally, with improved results in regional perturbation.

The importance of creating a set of models that not only history match the data but also preserve geological realism is essential. Adding information in the static model and defining the constraints bound correctly is necessary to achieve a realistic production forecast (Alpak et al. 2009, Alpak et al. 2011, Alpak et al. 2016, Rojas et al. 2014, Arnold et al. 2014)

For every reservoir model we must quantify the misfit between history and production data. The first step is to choose the production data that we want to match (e.g. production rates, bottom-hole pressure, water saturation, etc.).

The different types of data must be normalized to allow comparison, Normalized Quadratic Difference (NQD) is commonly used to do this (**Mesquita et al., 2015; Almeida et al, 2014**). For every production data “ d ” that we want to match, it is possible to measure the deviations between simulated models results and history data with the following Equation 1:

$$NQD_d = \frac{QD_d}{AQD_d} \quad \text{Equation 1}$$

where, the numerator is the quadratic deviation between history data and simulated data in each observed data point from data series and, the denominator is the acceptable quadratic deviation used to normalize the NQD.

Two approaches can be used, a Single Objective Function or Multiple Objective Function. The first is standard practice in the industry, and sums up all NQD functions from the same model, from different wells and measured properties as described in Equation 2:

$$SOF = \sum_{d=1}^n w_d \times NQD_d \quad \text{Equation 2}$$

where w_d is the weight given to the type of data and n is the number of types of data chosen to match.

However, several works (**Schulze-Riegert and Krosche. 2007, Hajizadeh et al, 2011, Christie, 2013; Hutahaeen et al., 2015; Mesquita et al. 2015; Caeiro et al. 2014; Almeida, 2014**) showed that the sum of the NQD values in a single objective

function reduces the sensitivity to variations in match quality in different parts of the reservoir across various production variables, potentially limiting the impact of local model changes to the overall history matching. To address this, a multi-objective function is used in history matching. We use the concept of multi-objective function because a model is considered acceptable only if all objective functions are between an acceptable range.

In multi-objective history matching, the NQD_d values can be evaluated singly or in groups. Examples of groups are: separating pressure terms and production rates into different groups as they are sensitive to different uncertain attributes (**Christie et al., 2013**).

In a complex reservoir modelling, it is important to understand how the uncertain parameters (input) impact production data (output). Because of the non-linearity between input and output, determining the most critical parameters demands a multivariate analysis, which permits the match of the desired objective function. In several works, this identification allowed the calculation of a likelihood function to update the initial uncertain probability function to a new posterior probability function (**Maschio and Schiozer, 2013; Maschio and Schiozer, 2014, Bertolini et al, 2015**).

Our proposed methodology reduces reservoir characterization uncertainty simultaneously using the Probability Perturbation Method for facies modelling and image perturbation with Co-Simulation for porosity and permeability modelling. We use a multivariate-objective function together with a multivariate sensitivity analysis to identify the most influential attributes and reservoir regions affecting the objective functions. Our method allows us to history match multiple scenarios while preserving all well data, production data and geological knowledge.

Note that other uncertainties should be evaluated to cover all possible scenarios, however this will be the subject of future studies.

2. THEORETICAL BACKGROUND

This chapter is conceived to introduce tools and ideas already present in industry, and extensively used on the proposed methodology. Some of those tools are: Co-Simulation, Probability Perturbation Method and the quantification of mismatch errors between history and simulated data using Normalized Quadratic Deviation.

a. Probability Perturbation Method

Previously to any history matching, a set of geostatistical realizations is created taking into account the information available (e.g.: well data, seismic, variograms, geologic knowledge, etc.). This initial information (B) allows the calculation of a prior probability $P(A|B)$, that is the probability of the unknown property A (e.g. there is a facies type in a grid block) occurring given other information B . This probability is easy to access by kriging estimation, creating a probability distribution of event A for each grid block. This realization is conditioned for static data but will probably not honor the dynamic data.

The Probability Perturbation Method (PPM) integrates soft or secondary data D , with the previous probability model $P(A|B)$ to get an updated conditional probability model $P(A|B,D)$, which makes any simulated value depend not only on data B but also on data D . In this work, $P(A|D)$ is the probability of facies type A occurring given dynamic data D . When a geostatistical realization generates good matches and we want to reproduce the facies spatial distribution of that image on the following

iterations, the geostatistical realization is used as secondary information on the Probability Perturbation Method in order to calculate the $P(A|D)$. Using that image we can apply an indicator random function model described by Equation 3:

$$I(\mathbf{u}) = \begin{cases} 1 & \text{if given event } A \text{ occurs at } \mathbf{u} \\ 0 & \text{else} \end{cases} \quad \text{Equation 3}$$

where $\mathbf{u} = (x, y, z) \in \text{reservoir model}$. Then the probability $P(A|D)$ can be calculated using Equation 4:

$$P(A|D) = (1 - r_D)I(\mathbf{u}) + r_DP(A) \in [0,1] \quad \text{Equation 4}$$

where r_D is a parameter between $[0,1]$ that controls how much the model is perturbed, and $P(A)$ is the global probability of event A occurring that can be measured in a global histogram. The r_D parameter is an important input in the methodology that says how much the geostatistical realization is retained; if $r_D = 0$, then $P(A|D) = I(\mathbf{u})$ and the geostatistical realization is retained in its entirety, however, if $r_D = 1$ then $P(A|D) = P(A)$ then a new equiprobable realization is generated.

To combine $P(A|B)$ and $P(A|D)$ into $P(A|B,D)$ Hoffman (2005) uses Equation 5, assuming that there is a conditional independence between B and D .

$$P(A|B,D) = \frac{\frac{1 - P(A)}{P(A)}}{\frac{1 - P(A)}{P(A)} + \left(\frac{1 - P(A|B)}{P(A|B)} \right) \left(\frac{1 - P(A|D)}{P(A|D)} \right)} \quad \text{Equation 5}$$

In the regional perturbation method, the value of r_D may change between regions, allowing only the spatial distribution of some regions to be restrained, keeping variability in the rest of the reservoir as high as possible.

In Hoffman and Caers (2005), a simple and synthetic case is performed where an initial realization is used to do the Probability Perturbation Method, however, different values of r_D are given to the two different regions (Figure 1), on the left one a value of $r_{D_1} = 0.80$ is used to give few weight to the realization chosen, but on the other hand, on the right region a value of $r_{D_2} = 0.05$ is used in order to restrain the spatial distribution of the realization chosen.

Figure 1 – Realization chosen in at right side and de $P(A|D)$ calculated in two regions with different value of r_D (in Hoffman and Caers, 2005)

A set of realizations was created and the frequency of occurrence of the “red” facies was calculated for each block. It is possible to see that the pattern was better restrained on the right side of the image.

Figure 2 – Average of 100 realizations from the regional method (in Hoffman and Caers 2005)

b. Sequential Gaussian Co-Simulation

The Sequential Gaussian Co-Simulation (co-SGS) algorithm is based on the MultiGaussian assumption of the variable. Thus, any local conditional expectation and conditional variance can be identified by simple kriging estimates. So, any local Gaussian distribution is totally defined with the conditional mean and variance and the sequential simulation proceeds by generating a realization of local distributions according to a random path.

Equation 6 shows the simple kriging co-estimation:

$$Y^*(u) - m_y = \sum_{\alpha=1}^n \lambda_{\alpha} [Y(u_{\alpha}) - m_y] + v[B(u) - m_B] \quad \text{Equation 6}$$

where $Y^*(u)$ represents the parameter Y to be simulated in point u , m_y represents the stationary mean of the parameter Y , $Y(u_{\alpha})$ are all the points simulated until that time, λ_{α} are the weights given to each point calculated by Kriging estimation, $B(u)$ is the

secondary variable in point u , m_B is the stationary mean of the parameter B and v is the correlation coefficient between variable Y and B . The correlation coefficient is an important parameter and measures how much the pattern should be honored in the following iteration. It can be compared with the parameter r_D from Probability Perturbation Method by Equation 7:

$$v = 1 - r_D \quad \text{Equation 7}$$

It can be between 0 and 1 and for values near 1 the pattern is fully respected. As long as the value decreases, some flexibility is given for the following images, making it possible for the user to explore other similar options for that spatial distribution of that property.

In Hoffman 2005, Collocated Co-Simulation was used to history match pressure data of a simple 5 spot production by updating permeability spatial distribution. By selecting the best realization and a correlation coefficient for each well it was possible to create a much better matched by guaranteeing that the local permeability would minimize the misfit in pressure data between the simulated data and history data.

In Figure 3, it is possible to see that the matched model better represents the permeability distribution in the reference and provides an extremely good match (cited from **Hoffman 2005**) (Figure 4).

Figure 3 – Reference, initial and matched models of permeability distribution (in Hoffman 2005)

Figure 4 – Pressure for reference, initial and matched models (in Hoffman 2005)

c. Normalized Quadratic Difference

In order to quantify the misfit between the model and the history data it is used a Normalized Quadratic Difference (Equation 1) is used as in (Mesquita et al., 2015; Almeida et al, 2014):

$$QD_d = \sum_{i=1}^t (Sim_i - Hist_i)^2_d \quad \text{Equation 8}$$

$$AQD_d = \sum_{i=1}^t (Tol \times Hist_i + C)^2_d \quad \text{Equation 9}$$

where, Sim_i is the simulated data and $Hist_i$ is the history data for an observed data point i for data type d . The Acceptable Quadratic Deviation (AQD) is calculated using a percentage of history data as an acceptable misfit, characterized by the value Tol . In some data types (e.g. water rate) a constant C should be added to the tolerance to avoid inconsistency when production rate is zero.

To plot the misfit between models and history data, we use the $NQDS_d$ value (Figure 5), which describes if the mean behavior of the well is above or below the history data. $NQDS_d$ is described by Equation 10 and Equation 11:

$$NQDS_d = \left(\frac{LD}{|LD|} \right)_d NQD_d \quad \text{Equation 10}$$

$$LD_d = \sum_{i=1}^t (Sim_i - Hist_i) \quad \text{Equation 11}$$

Figure 5– Schematic representation of NQDS

3. SENSITIVITY ANALYSIS FOR PETROPHYSICAL ATTRIBUTES IN HISTORY MATCHING

One of the major novelties proposed in this work is the sensitivity analysis built for petrophysical properties in history matching. It is widely known that heterogeneity greatly affects reservoir production, however, until this moment, changes were made taking into account engineer's understanding of the model behavior.

Even more difficult is to make changes while keeping a realistic geologic model by ensuring the continuity and relationship between petrophysical properties.

With this tool is possible to know which attributes and regions affect the objective functions we want to match. For categorical properties, we calculate the relative frequency in each cell of all facies to understand if there is a high occurrence of a

facies type in the chosen set of models. For continuous properties, the model with less values of the sum of NQD function is a good choice. A multivariate sensitivity analysis is performed by inducing changes in properties' spatial distribution using porosity and permeability multipliers. Different regions are defined in the reservoir, for this work Voronoi Volumes were used. Each region of the reservoir has a porosity and permeability multiplier, 2 attributes per region, a set of models is created when the combination of all attributes is changed between models.

Note that the models created with multipliers have no structural consistency because of the discontinuities between regions, but they are useful to understand the relationship between input and output in simulations and to make the required changes for the secondary image used in Co-Simulation. For every model, the multiplier value for each region is chosen randomly using the distributions described in Table 1. Figure 6 shows an example of creating these models.

Attribute	Distribution	Minimum	Maximum
Porosity	Uniform	0.5	1.5
Permeability	Uniform	0.5	3.0

Table 1 – Distribution of property multiplier

Figure 6- Example of porosity models created for sensitivity analysis

After creating the model we simulate them and calculate the correlation between the variation for the attribute for the region and the variation in the NQDS value. This correlation can be described by a correlation coefficient or represented by plotting in the X axis, the value of the attribute for that model, and in the Y axis the value of NQDS, as illustrated in Figure 7.

Figure 7– Plot between attribute and NQDS with good spread

Even if there is a high correlation coefficient between an attribute and NQDS, it may not be enough to guarantee that the solution will converge to a good fit. To see if the misfit is acceptable we analyze the variation in NQDS, to do this, the spread in NQDS values should:

- Fit a regression (linear or not) with a good correlation coefficient that covers the null value for NQDS.
- If the distribution of points plotted has a plateau, it must be equal to zero.

Figure 7 is an example of a plot with the potential to match the data in the following iteration. Contrastingly, Figure 8 shows a plot without the specifications needed to improve the dynamic data, so they should not be used as secondary variable for the image perturbation method.

Figure 8– Plot between attribute and NQDS with a bad spread

At this point we pick the regions and the attributes influencing the objective function. The new set of geostatistical realizations should preserve initial knowledge and assumptions, honoring the variograms, histograms and the relationship between different petrophysical properties. With a correct diagnostic it is possible to know if an uncertainty reduction, by performing a Co-Simulation on a specific attribute and region or, on the other hand, if a re-characterization is a wisely choice.

4. METHODOLOGY

Figure 9 presents the general methodology for history matching and is described below. The novelty presented in this work contributes mostly to Steps 3, 11 and 12.

Figure 9 – General methodology for history matching and uncertainty reduction (modified from Avansi et al. 2015b)

- STEP 1: The reservoir is characterized accounting for all uncertainties in uncertain attributes. The probability function distribution of each property must be correctly defined to reach the “true” solution. Uncertainty can be defined with discrete levels of uncertainty or with a probability distribution function.

- STEP 2: Define an acceptable misfit limit for each objective function. Once the range of acceptance is established, the misfit is normalized allowing the treatment of multiple objective functions simultaneously. Normalization is described further on.
- STEP 3: At this step, decide whether history matching or uncertainty reduction is preferable. Uncertainty reduction is designated for the objective of re-characterize the attributes taking into account the observed data, involving the probability redistribution of uncertainty levels and/or elimination of any level. On the other hand, history matching has the objective of finding the best matched models, normally with an optimization algorithm.
- STEP 4: Combine different levels of uncertainty to generate a set of models using either Discrete Latin Hypercube or, in the case of geostatistical realizations, Discretized Latin Hypercube with Geostatistical Realizations (DLHG) as suggested by **Schiozer et al. (2016)**.
- STEP 5: Simulate models.
- STEP 6: Evaluate the simulated response variability for every set of generated models. Normalized Quadratic Difference with Sign must be calculated for each objective simulation defined as described in section 2.c.
- STEP 7: The history-matching procedure concludes if the models exhibit acceptable behavior, and the application begins.
- STEP 8: Review simulation model to evaluate if the problem is in numeric model, for example, problems in productivity index, evaluate boundary conditions, aquifer etc.
- STEP 9: In some cases, neither the petrophysical properties nor attributes are enough to match the data. There can be cases where the simulation model must be reviewed,

for example; changing the productivity index of the well. This problem regularly occurs in fractured reservoirs.

- STEP 10: When, between the history matching, few or no models match the objective function, a new parameterization is considered. A priori evaluation identifies the influential attributes for the objective function.
- STEP 11: After identifying the influential attributes, a re-parameterization is done. Changing the limits of variability, enlarging the number of discrete levels or changing the probability distribution are some options in “review characterization”.
- STEP 12: At this step, if an uncertainty reduction was chosen in STEP 3, the probabilities can be redistributed, however, an optimization algorithm is used for history matching.
- STEP 13: When there are models that have all objective functions matched, we recommend now generating more models to increase the number of filtered models.
- STEP 14: Filter, to work only with the best matched models. The filtering is done by selecting the models that have all objective functions with a NQD below a chosen value. The choice of the cutoff value for NDQ is normally dependent on the type of data and may be based on engineering judgement. For complex real cases, for example, it is very difficult to match models with low values of NQD, but it is possible to relax the criteria based on the importance of each data. For example, for problematic wells regarding operational issues, greater values of NQD can be assigned.
- STEP 15: Use the filtered models for forecasting or risk analysis.

This work focuses on the spatial distribution of petrophysical properties, reason why the uncertainty on the remaining attributes has been reduced to a single level.

Herewith, any variability in simulated data is only due to the different geostatistical realizations generated.

As with the attributes, we can also reduce uncertainty or re-parameterize geostatistical reservoir images. For each objective function, the approach is according to the diagnosis step. Because geostatistical realizations can be optimized locally and using a multiple objective function, different objectives can be defined and, in a single step, a simultaneous re-parameterization or an uncertainty reduction can be done to match different objective functions.

We use uncertainty reduction when the objective function varies considerably and at least one geostatistical realization (GR) matches the data. This GR has the characteristics that we want to reproduce in the following iterations to ensure the decrease of variability and the representation of the “real” solution, for this reason we use a secondary image in the image perturbation method, for categorical or continuous properties.

Figure 10 presents a particular case of uncertainty reduction in geostatistical realizations:

Figure 10 - Flowchart for uncertainty reduction in geostatistical realization

- STEP 12.1: With the goals defined, choose a geostatistical realization that matches the objective functions. This image is used as a secondary variable in the Co-Simulation and Probability Perturbation Method.
- STEP 12.2: Perform the multivariate sensitivity analysis for petrophysical properties
- STEP 12.3: Guarantee that the relationship between attribution variation and output respect the requisites to match the data.
- STEP 12.4: Identify which attribute is more influential in the history matching process and follow the flowchart properly.
- STEP 12.5: Perform the Probability Perturbation Method (section 2a).
- STEP 12.6 and 12.7: Perform Collocated Co-Simulation as in section 2.b.

With the parameterization and perturbation defined, a new set of geostatistical realizations can be generated (STEP 4).

On the other hand, it is possible to reduce uncertainty in a specific region to improve a particular objective function while re-parameterizing another region to fix the variability of another objective function. When no models cover the solution, it is possible to use the two approaches in step 11.

Characterization review can be described with flowchart represented in Figure 11.

Figure 11 – Flowchart for characterization review

Usually during the history matching process some wells simulated data move away from the solution. A characterization review allows us to identify what changes should be made to the local characterization to correct the deviation:

- **STEP 11.1:** Selecting a base image. If an uncertainty reduction is done at the same time, it will be the image that matches those objective functions. If only re-parameterization is done, it can be the geostatistical realization with the minimum value of single objective function (SOF). **STEP 11.2:** The multivariate sensitivity analysis is done in the same way as for uncertainty reduction.

- STEP 11.3: With the cross-plot describing the relationship between variation of attributes and NQDS value we can see how many regions and attributes affect an objective function. A high number suggests cross-influence and is preferable to remove the constraints to recover the prior probability and simultaneously do a Co-Simulation with the influential regions and attributes in the following iteration, matching everything in one step. However, if a single attribute in a fixed region is the main responsible for the mismatch, a re-parameterization can be done locally.
- STEP 11.4: When there is a high cross-influence it is preferable to remove the perturbation from the previous iterations to restore the initial uncertainty, by using $P(A|B)$ on probability perturbation method or by giving a small value for correlation coefficient in Co-Simulation.
- STEP 11.5: In this case, Co-Simulation can be used to guarantee that the characteristics in the region match the data. The re-parameterization can take into account the cross-plot and the deviation needed for the base geostatistical realization chosen in step 11.1. Imposing a deviation means changing the local mean of the secondary image in the influential region using a multiplier. The best value to multiply is given by the cross-plot from the multivariate sensitivity analysis.

If permeability is an influential attribute, the spatial distribution of facies and porosity, that originated permeability image, should be kept, ensuring that porosity characteristics within each facies, and the permeability pdf within the porosity value is respected. However, a key point of our proposed methodology is that if porosity is the influential attribute, instead of permeability, it is only necessary to condition facies and porosity, keeping the permeability uncertainty as high as possible, reducing the risk of constraining the solution too much.

5. APPLICATION

To apply the proposed methodology we used the synthetic reservoir UNISIM-I-H (Avansi and Schiozer, 2015a), which is a benchmark case for history matching and uncertainty reduction studies. Despite being a synthetic case it uses real well data from the Namorado Field, in Campos Basin. The grid used in UNISIM-I-H is a corner-point with 81 x 58 x 20 cells (36.739 active cells) where each cell is 100 x 100 x 8 m.

The original oil in place (OOIP) volume is 132 million m³. The oil density is 27.72 °API, saturation pressure is 210.03 kgf/cm³ and reservoir temperature is 80 °C. Other characteristics can be found in Avansi and Schiozer (2015a)

The model has 11 horizontal production wells, 4 vertical productions and 11 vertical injection wells. It has 11 years of history data, where production wells have history data for the oil rate, water rate, liquid rate, and bottom-hole pressure, while injector wells have water injection rate and bottom-hole pressure history data. Figure 12 shows a representation of the reservoir model.

For history matching, in the simulation model the liquid rate is informed for producers while water injection rate is informed for injector wells.

Figure 12 – Facies distribution for case study UNISIM-I-H

We generated an initial set of 500 reservoir images. For each reservoir image we created a geostatistical realization of facies, net-to-gross ratio, porosity and permeability. Based on well log data, geostatistical modeling is done with the parameterization of variograms taking into account the well log data and correlation between properties.

Firstly, we defined the variograms of facies for each of the 3 types, and using Sequential Indicator Simulation, simulated facies property on every grid block of the reservoir. Secondly, we defined the variograms of porosity in each facies and simulated the property conditioned to the facies image using Sequential Gaussian Simulation. Finally, we simulated permeability using a joint distribution with porosity, and a cross-plot from the real reservoir data. For net-to-gross ratio, we gave a fixed value to each type of facies.

Each loop generated a set of 150 reservoir images, enough to explore the variability of the models.

We used Voronoi volumes to parameterize regions through the reservoir, we found this to be effective and easy to define.

Based on **Oliveira (2014)** we chose the correlation coefficient (CC), and used Equation 12 to express the value of the correlation coefficient depending on NQD value.

$$CC = 0.85^{1.5*NQD_{max}} \quad \textbf{Equation 12}$$

where NQD_{max} is the maximum value of NQD from all objective functions of a well for the region that we are establishing the correlation coefficient.

To match field production rate, field water injection rate and reservoir average pressure we ran a major global match for the field. With this, we could start local matching for each well.

6. RESULTS

We simulated the initial 500 reservoir images and analyzed the variability. We plotted pressure and production curves, shown in Figure 13 to 15, with Figures 16 and 17 showing the NQDS.

With this approach, we can understand the effect and initial variability in simulated data due to the petrophysical properties spatial distribution. Figure 16 shows that there is high variability in all objective functions (oil rate, water rate, liquid rate and bottom-hole pressure) from production wells in the first iteration.

Figure 13 – Average Field Pressure for 1st iteration

Figure 14 – Field liquid rate production for 1st iteration

Figure 15 – Field water injection rate for 1st iteration

Figure 16 – NQDS for liquid rate, oil rate, water rate and bottom-hole pressure for all production wells in 1st iteration

As seen in the figures, the majority of the models lack in liquid production and water injection rate in every well. To match the volumes of oil and water the production and injection volumes must be correct.

Figure 17 – NQDS for water injection rate and bottom-hole pressure for all injector wells in 1st iteration

We perturbed petrophysical properties sequentially. Facies and porosity were perturbed simultaneously and through the necessary regions. This set of perturbation was called iteration “A” and had 8 loops, each loop generating a set of 150 reservoir images. To generate permeability images we used only the variograms and cross-plot with porosity, however, since the porosity and probability distribution function was changed from its prior distribution, it affected the probability distribution function of permeability as well. The improvement in models is represented with NQDS charts in **Error! Reference source not found.** to 22.

It is possible to see that the reduction of the uncertainty in porosity, that consequently affected permeability probability distribution, improved the behavior of the production and injection wells. The behavior in each well is different, one reason is that if the porosity of a local region has now low values, permeability will be narrowed to low values also, however if porosity has higher values there is still a large variability between the possible range of values for permeability. However, the same process applied to porosity must be done to permeability to achieve a good history matching.

Figure 18 - Liquid rate for production wells between iteration 1 and A8

Figure 19 - Oil rate for production wells between iteration 1 and A8

Figure 20 – BHP of production wells between iteration 1 and A8

Figure 21 – BHP for injection wells between iteration 1 and A8

Figure 22 – Water injection rate between iteration 1 and A8

We then perturbed permeability to further reduce the uncertainty of the petrophysical property distribution. We did this in iteration “B” with 14 loops, again each loop generating 150 reservoir images. Through the application of the perturbation, we re-parameterized every time it was necessary, however, in many cases, it was done

together with a Co-Simulation in other wells. The final iteration was “B14”. At the end of the process, the models generated were notably better matched than the initial set of models. The improvement charts of NQDS are shown in Figure 23 to Figure 27 and the production curves of one well are presented in Figure 28 and Figure 29 before and after the application of our proposed methodology. In Figure 23 to 27 it can be seen that the variability has decreased in every well, while keeping solutions near a good match for every objective function.

Permeability greatly affects flux and reservoir production, it is possible to see that in PROD05 and INJ005, that only achieved a good match after perturbing the local permeability near the two wells. It was a particular difficult case to match, because they are very close wells, a small modification may truly impact the other well. Both wells were matched simultaneously with a reservoir image that would guaranty the convergence of them both.

Figure 23 - NQDS for liquid production rate

Figure 24 - NQDS for oil production rate

Figure 25 - NQDS for bottom-hole pressure of production rate

Figure 26 – NQDS for water injection rate

Figure 27 – NQDS of bottom-hole pressure for injection wells

Figure 28 – Oil rate production for PROD25A in first and last iteration

Figure 29- Water rate production for PROD25A in 1st and last iteration

In the work developed by Mesquita et al. 2015 is observable that is extremely important to have a consistent methodology to deal with geostatistical realizations because, normally, the initial set of reservoir images built with the prior probability will not match all objective functions at the same time, and no models will pass the filter in order to do risk analysis. In the uncertainty reduction done in Mesquita et al. 2015 at the end of the 16th iteration there are about 25% of the models that have all objective functions with a NQD value below 20, however there is no model below 5.

On the other hand, treating geostatistical realizations allowed us to have all models below 25 for all objective functions and, if the filter had a cut value of 5, 34 % of the models would be considered acceptable.

7. DISCUSSION AND CONCLUSIONS

The application of our methodology shows that spatial distribution of petrophysical properties has a positive impact in model performance and so should be considered in reservoir uncertainties and integrated into the workflow of history matching and uncertainty reduction.

The integration of geostatistical modeling, Co-Simulation and Probability Perturbation Method allowed us to generate multiple reservoir images equiprobable and better matched than the initial set generated with the prior probability distribution.

The regional multi-property image perturbation method is of most value because it allows us to perturb multiple and different types of petrophysical properties, whether categorical or continuous. It improves the reliability of reservoir characterization, since the models generated simultaneously respect all well log data, variograms, geological knowledge and dynamic data.

We efficiently, objectively and sequentially reduced uncertainty for various petrophysical properties using the multivariate sensitivity analysis. This analysis was based on other sensitivity analyses for prior uncertain attributes, adapted in this work for petrophysical properties. This tool, when used together with the perturbation method, greatly assisted understanding of the relationship between the input and output of the model. The multivariate sensitivity analysis has been useful not only to identify influential attributes and regions but also to re-parameterize regions from mismatched wells and to understand the cross-influence between reservoir characterization and simulated data.

Because we made regional perturbations, matching individual wells was possible without great interference to other wells.

Selecting which objective functions to match and the respective tolerances for an acceptable mismatch is crucial to converge to the “true” solution. Without due care to these two areas, the solution may diverge from history data while still honoring the NQD value. In future applications an objective function for the time of water breakthrough may be used to increase the reliability of the models generated after the history matching.

Further works may use a set of reservoir images to achieve the secondary information for probability perturbation method or for the Co-Simulation. Using only one image as secondary information may achieve convergence for a local minimum, making it difficult to minimize the NQD value for some individual objective functions. We also suggest that other uncertain attributes should be taken into account. Our results show that integrating different types of uncertainties with geostatistical modelling is a necessary and important step in the oil and gas industry.

ACKNOWLEDGMENTS

The authors are grateful to PETROBRAS, the research network SIGER, the National Agency of Petroleum, Natural Gas and Biofuels (ANP), the Center of Petroleum Studies (CEPETRO-UNICAMP) particularly the UNISIM research group, the Department of Energy of the School of Mechanical Engineering of the University of Campinas (DE-FEM-UNICAMP), the Foundation CMG and National Counsel of Technological and Scientific Development (CNPq), for supporting this research, and also, to the Computer Modelling Group (CMG) and Schlumberger for software licenses.

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