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# History matching by integrating regional multi-property image perturbation methods with a multivariate sensitivity analysis

Gonçalo Soares Oliveira*, Denis José Schiozer, Célio Maschio

*Department of Energy, Division of Petroleum Engineering, University of Campinas, PO Box 6122, Campinas, São Paulo 13083-970, Brazil*

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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 modelling.

## 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

* Corresponding author.

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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 and Soares (2007) and Mata-Lima (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 de 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, 2011, 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 Eq. (1):

$$NQD_d = \frac{QD_d}{AQD_d} \tag{1}$$

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 Eq. (2):

$$SOF = \sum_{d=1}^{n} w_d \times NQD_d \tag{2}$$

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 Kroschem, 2007; Hajizadeh et al., 2011; Christie et al., 2013; Hutahaean et al., 2015; Mesquita et al., 2015; Cairo et al., 2014; Almeida et al., 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, 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.

### 2.1. 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 $P(AB)$, 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 $P(A \mid B)$ to get an updated conditional probability model $P(A \mid B, D)$, which makes any simulated value depend not only on data $B$ but also on data $D$. In this work, $P(A \mid D)$ is the probability of facies type A occurring given