Geostatistical history matching with seismic data integration

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Abstract

This thesis intends to address a relevant problem of the oil and gas industry related with the modelling and characterization of hydrocarbon reservoirs that honour simultaneously existing historical production data and seismic reflection data, i.e. the integration of seismic reflection data into history matching. By honouring all available data the resulting reservoir models have a better chance to predict the reservoir behaviour. The proposed geostatistical history matching with seismic data integration procedure is an iterative methodology based on a genetic algorithm, acting as a global optimizer, where the perturbation of the models parameters is performed recurring to stochastic sequential simulation and co-simulation. The proposed workflow starts with the stochastic simulation of petro-elastic models, forward modelling and the comparison against the observed seismic and production data and the simulated ones. The definition of areas of influence for each well was tackled by two different approaches. According to a geometric criteria and based on the non-linear relationship between the model parameters (permeability) and the state variables (production deviations) in terms of correlation coefficients. The selection of the conditioning data for the next iterations is based on the petro-elastic ensemble simulated at the current iteration with better response in the MDS.

Keywords: History Matching, Geostatistical modelling, seismic data integration, reservoir characterization.

1. Introduction

Reservoir modelling is by far not a trivial task since the resulting reservoir model should represent, in a reliable way, the reservoir characteristics (internal petrophysical properties) in order to be used as input to key reservoir management decisions. The input data (both static and dynamic) are collected under extreme conditions which may lead to substantial uncertainty in the measurements and interpretation of the data. Hence, stochastic approach is a natural solution of the reservoir modelling problem. The integration of static data (well-log and seismic reflection data) is usually performed recurring to geostatistical tools but when it comes to the integration of dynamic data into reservoir modelling, traditionally referred to as history matching, some problems comes up due to the highly non-linear relationship between the static model and the fluid production. The history match is an ill-posed problem, nonlinear and with non-unique solution where different models can match the observed historic production data. Thus, it is not surprising that the predictability of these reservoir models are often very poor.

This work, by integrating the seismic reflection data within the geostatistical history matching, aims to simultaneously solve both inverse problems (history matching and seismic inversion) as a result of the simultaneous match towards the observed seismic reflection and historic production data while the history matching is performed, which allows the improvement of the reservoir predictions and to quantify and capture the modelling uncertainties.

2. Geostatistical reservoir modelling

Nowadays, the importance of using geostatistical tools as part of reservoir geo-modelling workflow is mainly due to enabling the integration within the same framework of data with different scale support and volume: well-log and seismic reflection data; that in early stages of geostatistical modelling provides trends of the subsurface geological properties by reproducing the highest and lowest values in areas near wells locations and the estimation through the seismic reflection data of the subsurface geological properties in all reservoir extension due to its higher spatial coverage.

The seismic reflection data only contains indirect measurements of the subsurface geology and its relationship with the subsurface petrophysical properties is non-linear and approached as an inverse problem. Therefore, geostatistical tools are the solution in order to obtain resulting inverted models able to reproduce the highest and lowest values in all reservoir extension, allowing reducing the uncertainty in areas far from the wells locations and allowing more detailed, heterogenic and reliable models when compared with those models based exclusively from well-log data.

The inference of an unknown value,$Z(\boldsymbol{u})^*$ at a certain location $\boldsymbol{u}$ given a set of experimental data can be achieved through sequential stochastic simulation algorithms. Direct sequential simulation and co-simulation with joint probabilities distributions are sequential stochastic simulation algorithms able to overcome the other stochastic approaches due to the capacity of reproducing all the values retrieved from the experimental data, as well as to ensure the reproduction of the experimental joint probability distribution between the primary and the secondary variables on the simulated models and the reproduction of the experimental bivariate cumulative distribution function between the primary and secondary variables even when the correlation between them is low (Deutsch and Journel 1998; Soares 2006).

2.1. Geostatistical seismic reflection data integration

The integration of seismic reflection data can be achieved through the geostatistical framework which starts by inferring the subsurface elastic properties (e.g. acoustic and/or elastic properties). Transform seismic reflection data into petrophysical properties is an inverse problem, where is only known the response of a particular Earth's system to a limited set of indirect measurements, which tries to infer the parameters of the system in study that give rise to that solution (Tarantola 2005; Bosch et al. 2010).

The indirect geophysical measurements or observations ($\boldsymbol{d_{obs}} \in \boldsymbol{R^s}$) which are normally contaminated by some errors ($\boldsymbol{e}$) originated from different sources and the model parameter space of the subsurface properties of interest ($\boldsymbol{m} \in \boldsymbol{R^n}$) are related by a forward model (F) that may be expressed as next (Tarantola 2005):

$$d_{obs} = F(m) + e \qquad (2.1)$$

The forward model, F, can be written in the following form:

$$A = r * w \qquad (2.2)$$

Where A are the recorded seismic amplitudes, r are the subsurface reflections coefficients that are convolved with a wavelet w.

Global Stochastic Inversion (GSI)

The Global Stochastic Inversion (GSI; Soares et al. 2007; Caetano 2009) is an iterative geostatistical methodology based on two main ideas: the used, at the end of each iteration, of a global optimizer based on a genetic algorithm with the cross-over principle; and the perturbation of the inverted models with stochastic sequential simulation (DSS and co-DSS). The general outline of this iterative geostatistical methodology is present in the next Figure 1:

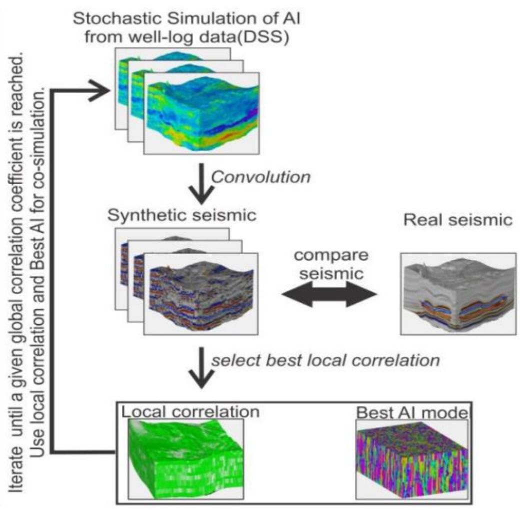

Figure 1 - Schematic representation of the Global Stochastic Inversion methodology (Azevedo 2013).

2.2. History Matching

The integration of dynamic data into petrophysical models of petroleum reservoirs is traditionally conducted by history matching techniques which allows the calibration of the static model to a known dynamic data by tuning the reservoir model petrophysical properties (Mata-Lima 2008).

The history matching is an inverse problem, where the reservoir dynamic response is known in terms of flow rates and pressure but the conditions that originate such result are unknown, such as the parameters spatial distribution e.g. permeability and porosity. The history matching is also an ill-posed problem, very nonlinear and with non-unique solution, that can lead to a multiple combinations of the model parameters and reproduce equally good history matched models which may feature different geological and petrophysical properties, i.e. different variable combinations of reservoir model that generate a good match to the production data with the same degree of accuracy (Gomes and Alves 2013; Caeiro 2014).

Classical approach to history matching

Traditionally, the main idea behind most history matching procedures is to perturb the model parameter space within an iterative procedure: (i) initially it is characterize the reservoir petrophysical properties by taking into account the prior knowledge (static model); then (ii) fluid flow simulation (dynamic model) is run on the previous models to obtain the simulated production history; (iii) the comparison between the simulated historical production data from each model and the real historical production data is done according to a mathematical expression, the objective function, that measures the difference between the observed production and the simulated production:

$$Mf = \frac{1}{2}\sum_{i=0}^{N}\frac{(obs_i - sim_i)^2}{\sigma_i^2} \qquad (2.3)$$

Where, at time=i, obs_i is the observed or historical data (e.g. rate or pressure) and sim_i is the simulated results. *N* refers to the number of measurements (the amount of time steps where the measurement was made) and σ_i the measurement error in the observed data (goodness function); and (iv) create a perturbation in the initial model with the information obtained from the objective function and repeats all the previous steps until a minimum value of the objective function is achieved.

3. Geostatistical history matching integrating seismic reflection data

Generating Earth models able to fit both recorded seismic reflection and historic production data is essential to better hydrocarbon reservoir characterization and its forecast. Commonly, both processes are approached in separate workflows where each type of data is matched individually (Azevedo 2013).

The petro-elastic models obtained from geostatistical seismic inversion algorithms are able to match the observed seismic data, however in mature fields they may start to show some incapacity within the history matching process since while is tuning the reservoir models to match the observed production data, the resulting petro-elastic models starts to diverge from the observed seismic reflection data. This event is more evident at locations far from the wells, where the constraining data is fewer. Therefore, it is proposed a geostatistical history matching methodology where the seismic data is integrated as part of the history matching procedure. This integrated methodology is based on a genetic algorithm, acting as a global optimizer, where the selection of the conditioning data for the next iterations is based on the petro-elastic ensemble simulated at the current iteration with better response in the MDS and the perturbation of the models parameters is performed recurring to stochastic sequential simulation and co-simulation.

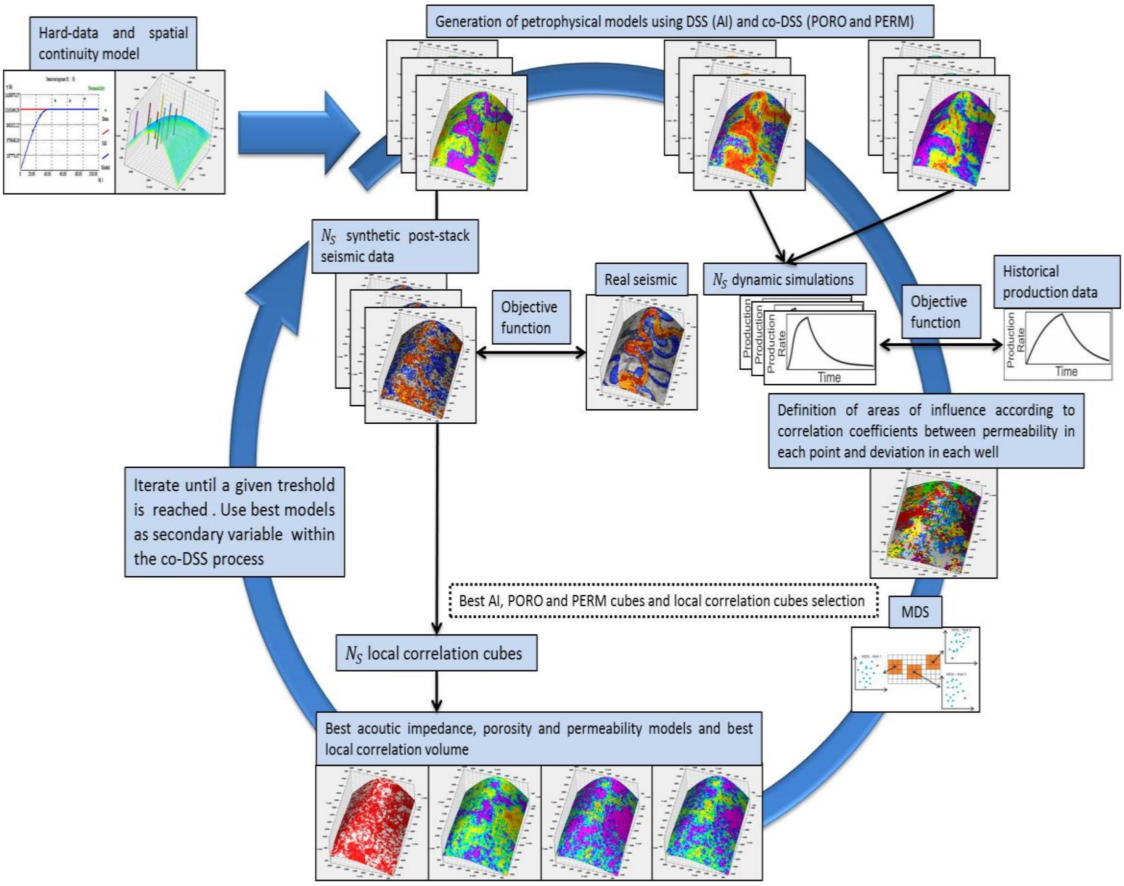

Figure 2 - General framework of the proposed methodology with the integration of seismic data.

The proposed methodology can be divided in two approaches: the geostatistical history matching (Section 3.1) and the geostatistical history matching with seismic data integration (Section 3.2).

3.1. Geostatistical history matching

The implementation of this methodology is firstly based on the prior information, and from the study of well-log data values and spatial continuity allows to assume the properties distribution and the spatial continuity pattern (imposed by the variogram model) of the reservoir at the same time. By taking into account the initial study regarding the prior information it is performed the stochastic sequential simulation algorithm, DSS, by generating N_s equiprobable petrophysical models. Then, through the dynamic response obtained from the dynamic fluid flow simulation of each simulated model is possible to evaluate how well the model can reproduce the real historic production data by taking into account the values of pressure and water production from each well for each time, the multi-criteria objective function, M:

$$M = \sum wells \sum WBHP, WWPR \sum time \frac{\left(q_{ijk}^{obs} - q_{ijk}^{sim}\right)^2}{2\sigma_{ij}^2} \quad (3.1)$$

Where q_{ijk}^{obs} are the observed values, q_{ijk}^{sim} are the simulated values, σ_{ij}^2 the data variance, WBHP the well bottom hole pressure, and WWPR the well water production rate.

Then by defining areas of influence around each well it is performed a local perturbation with the objective of using the best composed models to define patches around each well considering only the ones with the closest dynamic response through the previous multi-criteria objective function. This best composed models will be used as secondary variable for the co-simulation for the next iteration. While perturbing the model parameters space with the generation of new reservoir models using the previous simulation model as soft data, this iterative process aims to achieve a faster convergence of the resulting models by decreasing the difference between simulated and observed historical production data.

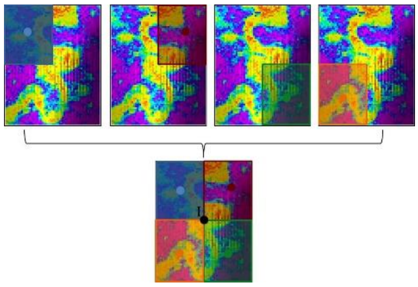

Figure 3 - Best composed image representation applied to a reservoir were the wells distribution comprises a five spot strategy (4 producer wells and 1 injector well).

The criteria herein used consist into a symmetric division of the reservoir space for each well constraining all the reservoir to match towards the historical production data. One of the problems related history matching is the loss of prior information by tuning the reservoir petrophysical properties, i.e. the loss of the properties spatial continuity pattern. As a consequence, the consistency between the static data and the resulting simulated models may not be reproduced. Therefore, in order to tackle this problem, it is proposed a new way to define the areas of influence, according to: (i) geometric criteria and (ii) correlation coefficients between the ensemble of the petrophysical properties and the deviations between real and simulated production responses. Thus, by considering different definitions of areas of influence and with the seismic data integration (Section 3.2) is possible to guarantee a better reproduction of the reservoir properties by matching not only the historic production data but also the observed seismic reflection data.

3.2. Geostatistical history matching with seismic data integration

Besides the simplicity of implementation and faster convergence in geostatistical history matching while the model parameter space is tuned to match the observed production data, the resulting petro-elastic models may start to diverge from the observed seismic data. This is more evident at locations far from the wells, where the constraining data is fewer, making this models less suitable to predict the reservoir behaviour since the misfit between observed and simulated production data are only known at sparse locations (well locations).

The proposed workflow may be divided in three different stages: (i) the stochastic simulation of petro-elastic models, forward modelling and the comparison against the observed seismic and production data; (ii) the definition of areas of influence according to geometric criteria (radius of influence) and the definition of influence areas according to correlation coefficients between the ensemble of the petrophysical properties and the deviations between real and simulated production responses; (iii) the selection of the conditioning data for the next iterations based on the petro-elastic ensemble simulated at the current iteration with better response in the MDS by taking into account a multi-objective function:

$$Mf = W_{sy} \times \sqrt{\sum_{i,j=1}^{N_s} \frac{1-(\rho_{ir}+\rho_{jr})}{2}} + W_{dy} \times \sum_{i,j=1}^{N_s} \frac{(x_{ir}-x_{jr})^2}{2\sigma_i^2}, r = 1, \dots, R \qquad (3.2)$$

Where R is the total number of wells, the ρ_{ir} and ρ_{jr}, and the x_{ir} and x_{jr} are both responses of the ensemble of models comprising the N_s simulated seismic and production models with the real seismic reflection data and the historical production data respectively for a given well (r); σ_i is the deviation assumed for the historical production data; W_{sy} and W_{dy} are user-defined weights defined for seismic and dynamic data respectively. These models are patchwork models created through the selection of best-fit regions from the set of simulated models which ensure the lowest misfit between observed and synthetic data for both, recorded seismic reflection and observed historical production data.

4. Case study

The proposed methodology was developed and implemented in a synthetic reservoir, the Stanford VI reservoir (SVI; Castro et al. 2005), where only Layer 2 was considered.

The reservoir is an asymmetric anticline comprising meandering channels of variable sizes with four facies types: floodplain, point bar, channel and boundaries; and no faulting, composed by 90 thousand cells $(60 \times 75 \times 20)$ where each cell as the dimension of $50 \times 50 \times 2$ meters in the *i, j, k* directions, respectively. The dataset comprises, along with the well set, the true three-dimensional models of acoustic impedance, porosity and permeability as well as a noise-free full-stack seismic volume.

The original synthetic dataset, assumed as real data within this thesis, is composed by a set of 23 wells from where only 12 were used to constraint the geological history matching with seismic data integration, while the rest of the wells were not used in any part of the procedure. The reservoir production start due to the existent pressure supported by the aquifer and it was in production during approximately 3 years, from February 1st, 1975 until December 15th, 1977. The 12 production wells were located preferentially in the Western part of the model.

5. Results

The results presented in this section may be divided into two parts, depending on the influence well criteria used: geometric criteria (Section 5.1) and according to the correlation coefficients between permeability in each grid point and deviation in each well (Section 5.2). Those areas, surrounding or far away from the wells location can have a huge impact within the proposed methodology, and each criteria is performed differently within the geostatistical history matching with seismic data integration in order to assess the stability of the proposed methodology to the regionalization model.

5.1. Geometric criteria

By considering the definition of areas of influence according to a radius of influence, the areas outside the areas of influence of each well are only conditioned to the seismic inversion, i.e. the convergence of those areas are only conditioned to the seismic inversion convergence and the areas inside those areas are simultaneously conditioned to both seismic and historic production data. The convergence was reached after 10 iterations with 16 ensembles of petro-elastic models: acoustic impedance, porosity and permeability; which were simulated and co-simulated per iteration.

Different sizes of the area of influence of each well has different impact on the resulting inverted petro-elastic models: smaller influence areas allow the reproduction with more accuracy and detail of the high variability of the real petro-elastic models, i.e. the small and large scale non-stationary patterns; while in other hand, (on the top of the figures) higher well size influence definition are only able to reproduce the main features, the large scale non-stationary patterns (Figure 4). Therefore reflecting the importance of the seismic as part of the iterative geostatistical procedure.

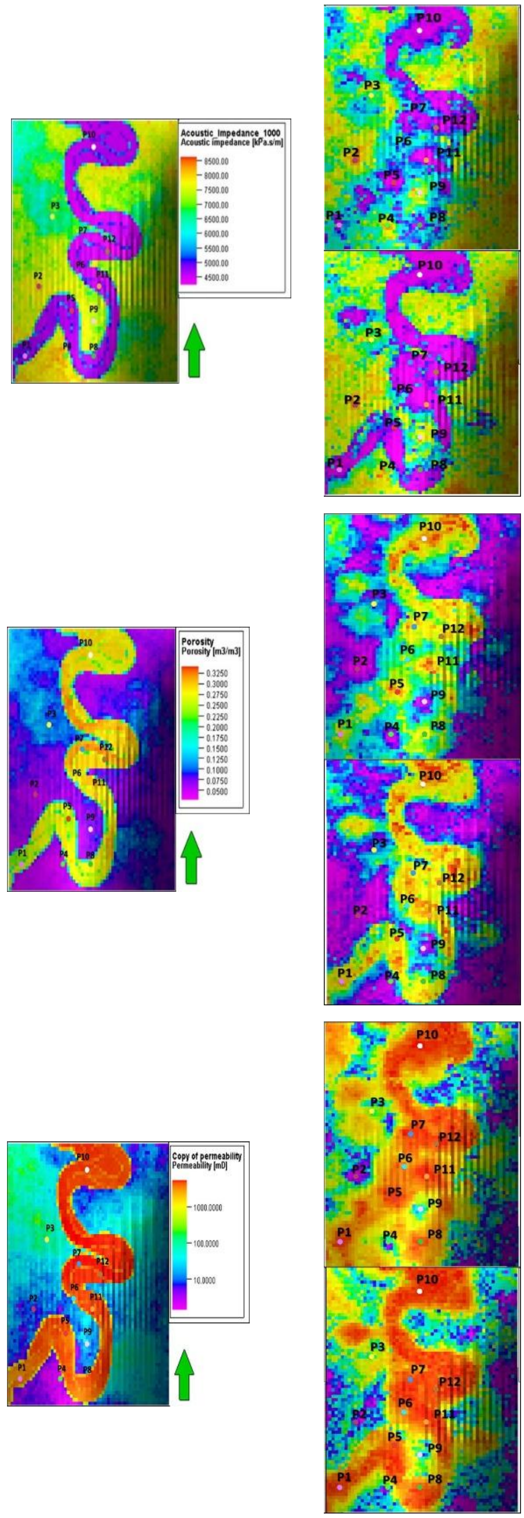

Figure 4 - Horizontal sections extracted from left to right: the real petro-elastic models and the inverted petro-elastic models. (On the top) for the larger area of influence and (on the bottom) the small area of influence.

The resulting synthetic seismic volume are able to reproduce approximately the non-stationary patterns related with the meandering channels reproducing its high variability in terms of shape and thickness (Figure 5).

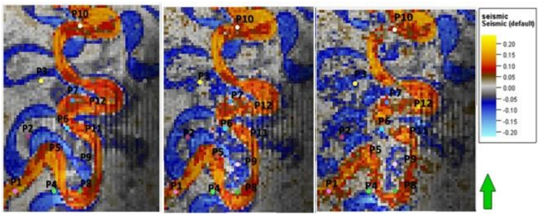

Figure 5 - Horizontal sections extracted from (left) the real seismic data, (middle) the synthetic seismic with less area of influence and (right) the synthetic seismic with higher area of influence at the end of the iterative geostatistical process.

Since this thesis aims to solve simultaneously two different non-linear inverse problems, through the best local correlation cube created at the end of each iteration it is possible to interpret the evolution of the convergence methodology by visually inspecting the best local correlation coefficients volumes computed at the end of each iteration (Figure 6).

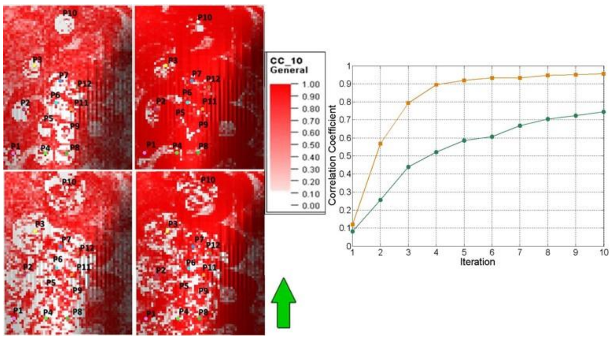

Figure 6 - Horizontal sections extracted from the best local correlation volume (top) for the smaller well size influence and (bottom) for the higher well size influence at the end of: (from left to right) iteration 1 and iteration10. On the right, the correlation coefficient evolution for each one, were the green curve refers to the higher well size influence and the orange curve to the smaller well size influence.

The convergence in terms of WBHP and WWPR are also very good for both cases, reflecting that the match towards the historic production data has been achieved.

5.2. According to correlation coefficients between permeability in each grid point and deviation in each well

Due to the non-uniqueness nature of the history matching problems ensuring a small deviation over the production profiles, it does not ensure how the retrieved petrophysical models are close to the real solution. The definition of well influence according to correlation coefficients between permeability in each grid point and the deviations over the simulated and real historic production data in each one of the wells allows to constrain all grid cells to the match towards the historic production and the seismic data simultaneously.

The proposed methodology is highly dependent on the convergence of both, however this does not guarantee the reproduction of the main geological features of the inverted petro-elastic models, acoustic impedance, porosity and permeability. Therefore, different dynamic and seismic weights were considered, i.e. more or less seismic influence within the iterative geostatistical procedure.

The convergence was reached after 6 iterations with 32 ensembles of petro-elastic models: acoustic impedance, porosity and permeability; which were simulated and co-simulated per iteration. By considering higher seismic influence, as the iterative geostatistical procedure gradually increases its convergence the reproduction of the large and some of small scale non-stationary patterns is clearly (Figure 7). At the end the iterative geostatistical procedure, the synthetic seismic volume were it was considered the seismic higher weight is able to reproduce more approximately the non-stationary patterns related with the meandering channels and its high variability in terms of shape and thickness (on the right of the Figure 8).

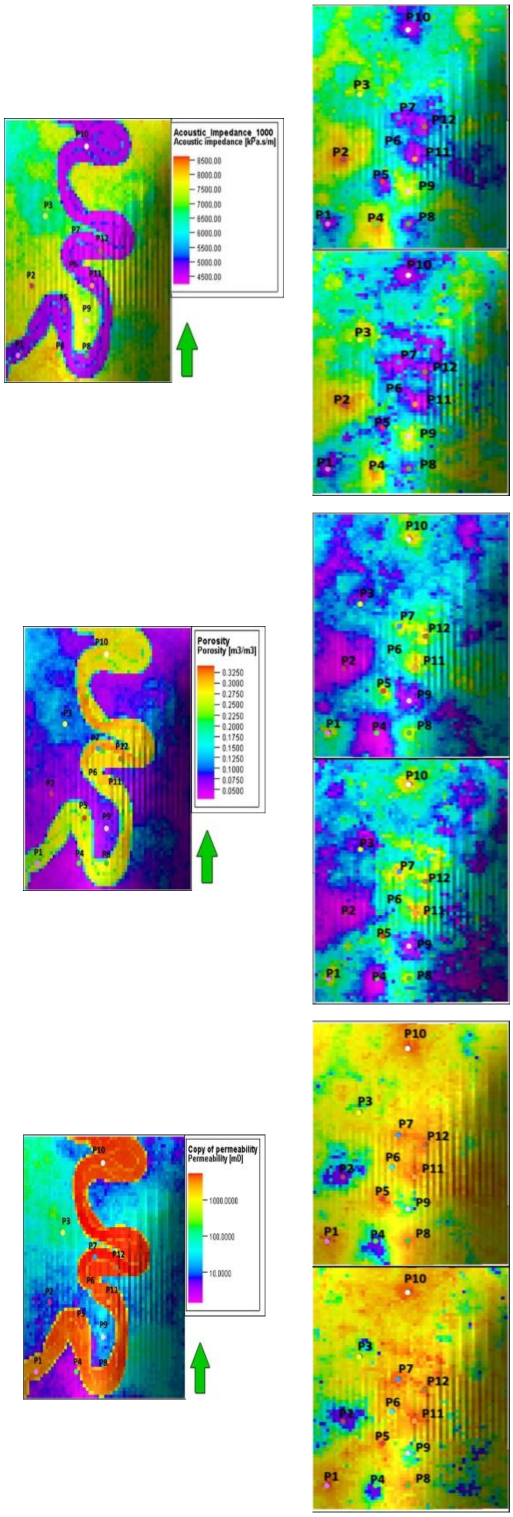

Figure 7 - Horizontal sections extracted from left to right: the real petro-elastic models and the inverted petro-elastic models. (On the top) with less seismic influence and (on the bottom) with higher seismic influence.

At the end the iterative geostatistical procedure, the synthetic seismic volume were it was considered the seismic higher weight is able to reproduce more approximately the non-stationary patterns related with the meandering channels and its high variability in terms of shape and thickness (on the right of the Figure 8). In the other hand, when is lower the synthetic seismic volume cannot reproduce accurately the non-stationary patterns but only some proportions without continuity (on the middle of the Figure 8).

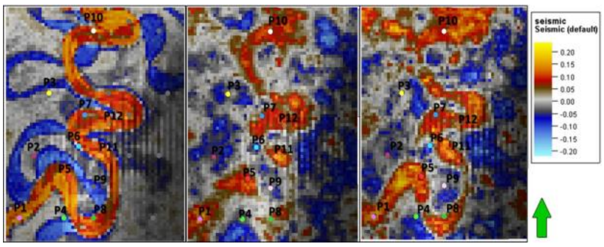

Figure 8 - Horizontal sections extracted from (left) the real seismic data, (middle) the synthetic seismic with less seismic weight and (right) the synthetic seismic with higher seismic weight at the end of the iterative geostatistical process at different depths.

The convergence in terms of WBHP and WWPR is different for different seismic influence in the multi-objective function as expected, since with less seismic influence and consequently higher dynamic influence the match towards the historic production is better. The impact of higher or less seismic influence within the iterative geostatistical procedure may be assesses through the convergence in terms of the objective function as the Figure 9 shows.

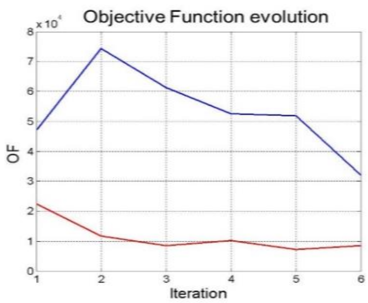

Figure 9 - Multi-**o**bjective function evolution at the end of each iteration for the geostatistical history

matching with seismic data integration: (the red line) with less seismic influence and (the blue line) with more dynamic influence.

Another way to recognize that the parameter model space is considerably well explored by all the models computed during the iterative geostatistical procedure, is by plotting all the models of each well from the first and the last iteration. This reduced space was created by retaining the first 2 eigenvalues that explain about 70% variance of the original model space. By plotting the dimension 1 versus dimension 2 it is easily recognizable that the algorithm is converging towards the real model response along the iterative procedure. It was considered only the well P3 from the 12 wells in Figure 10.

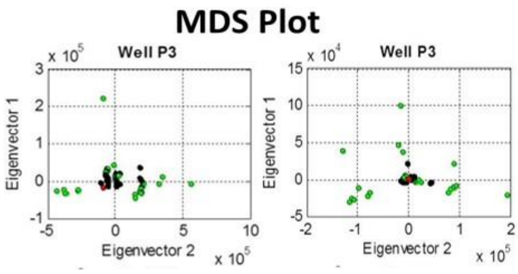

Figure 10 – MDS plot for all models produced in the first iteration (green circles) and the last iteration (black circles) well P3: (on the left) the case were it is considered higher seismic influence and (on the right) the case were it is considered less seismic influence. The true models are represented by the red circle

6. Summary and Conclusions

The implementation of the geostatistical history matching with seismic data integration is very promising since the results from different areas of influence are consistent with the real petro-elastic models. In the inverted petro-elastic model, the major patterns are reproduce even though it is difficult to represent reservoir models with non-stationary patterns associated with meandering channels.

It was studied two different criteria's in order to define the areas of influence of each well, and the areas constrained to the radius influence besides reproducing better the properties spatial distribution does not constrain all the reservoir extension to both inverse problems, while the other criteria constrain and are able to solve both inverse problems in all reservoir extension as well as to reproduce the major properties spatial distributions when it is taken into account higher seismic influence in the multi-objective function.

7. References

Azevedo, Leonardo (2013) "Geostatistical methods for integrating seismic reflection data into subsurface Earth models", PhD Thesis, Instituto Superior Técnico, Portugal

Bosch, M., Mukerji, T, González, E. (2010) "Seismic inversion for reservoir properties combining statistical rock physics and geostatistics: A review" *Geophysics Vol. 75*, ResearchGate

Caers, Jeff (2005) "Petroleum Geostatistics" SPE

Caeiro, Maria Helena (2014) "Optimised history matching using non-stationary geostatistical modelling", PhD Thesis, Instituto Superior Técnico, Portugal

Deutsch, C. and A.G. Journel (1998) "GSLIB: Geostatistical Software Library and User's Guide." Oxford University Press

Hoffman, Todd (2005) "Geologically consistent history matching while perturbing facies" PhD Thesis, Institute of Petroleum Engineering, Herriot Watt University, UK

Mata-Lima, Herlander (2008) "Reservoir characterization with iterative direct sequential co-simulation: integrating fluid dynamic data into stochastic model" Journal of Petroleum Science and Engineering. 62, 59-72.

Soares, Amílcar (2001) "Direct Sequential Simulation and Cosimulation" Mathematical Geology, Vol. 33, No. 8.

Soares, Amilcar, Diet, J.D. and Guerreiro, Luis (2007) “Stochastic Inversion with a Global Perturbation Method”, EAGE

Tarantola, Albert (2005) “Inverse Problem Theory” SIAM