Assessing geological and seismic interpretation uncertainty in a Geostatistical Seismic Inversion framework

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Abstract

Seismic Inversion is a key step in any exploration project and allow us to infer about the spatial distribution of a property of interest (e.g., acoustic impedance, porosity) combining well-log information and seismic reflection data, to help engineers make reliable decisions during field development. However, seismic inversion problems are ill-conditioned, nonlinear and with non-unique solutions, and deeply emerged in uncertainty, that propagates along the entire inversion procedure. It is very important to consider this uncertainty and be aware of the risks before making any inaccurate decision that might jeopardize the exploration project. In opposition to deterministic seismic inversion, geostatistical ones do not aim to get a single accurate/"best-fit" solution to describe the subsurface geology, instead generate a set of possible scenarios and therefore assess some levels of underlying uncertainty. This project proposes a methodology that combines an iterative geostatistical seismic inversion methodology, adaptive stochastic sampling and Bayesian inference algorithms for parameter optimization and uncertainty quantification. The novelty in this work is the addition of a stochastic regionalization of the inversion grid allowing assessing the uncertainty derived from the seismic interpretation, previously ignored. To better understanding the impact of stochastic regionalization over different geological backgrounds and to broaden the uncertainty envelope over the seismic interpretation process, this project is composed by two different approaches. The first assumes linearity of the seismic units, therefore optimizing the vertical positioning of the region's interfaces, the other one allows understanding the uncertainty over more heterogenic geological environments, by optimizing a set of multipliers for the region's interfaces (centred at a fixed vertical position). These novel approaches were performed in a real case study from an onshore Middle East field and based on the provided information (well-log data and seismic reflection data), the retrieved models aim to be more geologically consistent using this methodology. Both approaches shown good results of mismatch between retrieved models and unconditional hard-data and a tool for future work and different datasets.

Keywords: Reservoir characterization, Seismic Inversion, Uncertainty, Global Stochastic Inversion, Particle Swarm Optimization, Stochastic Regionalization

Introduction

One of the main concerns during an E&P project is to have an inaccurate description of the study area. There are too many steps full of uncertainty, related to human interpretation, instrumentation or methodological errors, scarcity of experimental data to the vague (but sometimes helpful) assumptions, etc. During decision making is very important to have a holistic point of view of all the possibilities, all scenarios, or else it results in a loss of large amount of money to exploration companies.

The focus of this work is the seismic inversion procedure, a well-known technique in the industry for more than 40 years. This powerful tool, independently of its variations, can combine the information given by the mildly accurate but sparse *well-log data*, with the well-covered but with lower vertical resolution, the *seismic reflection data*.

It is common practice in this industry to make use of deterministic seismic inversion (Cooke & Cant, 2010) procedures that generate a single "best-fit" solution, taking this as an undoubtable description of the reservoir (lack of uncertainty). To surpass this limitation, seismic inversion techniques were extended to a statistical framework, and allowing generation of subsurface models while assessing the uncertainty.

The present project aims to, simultaneously, assess local and global uncertainty and integrate well-log data and seismic reflection data, through an iterative geostatistical seismic inversion methodology. For this specific case, it's going to be implemented the Global Stochastic Inversion (Soares, Diet, & Guerreiro, 2007) algorithm that incorporates sequential (co-) simulation techniques (Direct Sequential Simulation) to generate Acoustic impedance (Ip) models, taking into account the log information from one single conditioning well and a 3D seismic reflection data from an onshore Middle East field.

Recently, Azevedo *et al.* (2015) proposed a methodology of a multi-scale assessment by integrating stochastic adaptive sampling and Bayesian inference (Mohamed et al.,2009) to adjust geological parameters, assuming stationarity along the entire inversion grid, which can be a dangerous assumption in more heterogeneous depositional environments and does not reflect the effects of layering. This stationarity assumption was relaxed by Nunes *et al.* (2016) by introducing a regionalization of the study area, therefore considering only stationarity at each sub-region, in this case, invariant local variogram model and probability distribution.

This thesis, inspired by both works of Azevedo *et al.* (2015) and Nunes *et al.* (2016), extends both methodologies by including uncertainty quantification of the location of the interfaces between each sub-region, as well as, the large-scale geological parameters related to the spatial continuity pattern (horizontal and vertical variogram range) and the probability distribution of *Ip.*

The fitness of each model is evaluated by quantifying how the synthetic seismic reflection data matches the recorded one, and if the inverted *Ip* models match with the non-condition *Ip* logs, at well locations. A real reservoir from onshore Middle East is used to illustrate the proposed method.

This work encompasses iterative geostatistical seismic inversion methodologies coupled with adaptive stochastic sampling and Bayesian inference algorithms (for uncertainty assessment) and a stochastic regionalization of the study area.

The main goals of this novel approach can be summarized by the following:

- Develop and implement a methodology for stochastic regionalization of the study area, along with an uncertainty assessment of seismic interpretation;
- Test the local stationarity assumption in a stochastic regionalization scenario;
- Assess small-scale spatial uncertainty by making use of iterative geostatistical seismic inversion (GSI) and at a large-scale by integrating adaptive sampling and Bayesian inference to tune the geological parameters;
- Generate inverted models that describe the spatial distribution of the petroelastic property, and simultaneously, describe the uncertainties related to measurement errors, and differences in scale of the available data (well-log vs. seismic);

Global Stochastic Inversion

The Global Stochastic Inversion (GSI) is based on a global perturbation method, instead of trace-by-trace, to minimize a given objective function defined as the mismatch between synthetic and real seismic traces (Caetano, 2012).

In this inversion method several realizations Ip are generated from where reflection coefficients are computed. These are then convolved with a known wavelet and compared, in a trace-by-trace basis, against the real seismic model.

In these algorithms, we visit every trace and for all the realizations we retain the "best" simulated trace (in an iterative process), for each location, based on the match of an objective function (function that measures the similitude between real seismic trace and the synthetic seismogram). The sequential process continues until every trace is visited and selected for simulation and transformation. (Soares, Diet, & Guerreiro, 2007)

The "best" traces of simulated *Ip* (that generated the synthetic seismic traces) are incorporated as "real" data for the next iteration (Caetano, 2012).

The GSI method focus on two major points: to use Direct Sequential simulation (DSS) and Co-DSS algorithms to generate and transform 3D *Ip* models, and the application of a genetic optimizer to converge the transformed *Ip* images into a minimum objective function. (Soares, Diet, & Guerreiro, 2007)

After that, we can summarize the GSI algorithm into:

1. Generation of a set of *Ip* realizations by using DSS, considering the information given by the well-log data;
2. Generation of a set of synthetic seismogram, by convolving the reflectivity series $r(t)$ (derived from the *Ip* models) with a representative source wavelet;
3. Calculate the fitness function between the synthetic seismogram and the real seismic. The match between both can

be expressed by the local correlation coefficients (CC);

4. Compose an auxiliary model by merging the selected “best” parts (cells with higher correlation coefficient) of all realizations for each location in the volume. The result is a “*Best Ip cube”* and a “*Best CC cube”*, composed by the cells with higher CC and respective value;
5. In the next iteration, generate a new set of *Ip* realizations by Co-DSS between both well-log and the previous “Best *Ip* cube”, as secondary variable. The global correlation coefficient of the previous *Ip* image, dictates the affinity criterion to create the next generation of images;
6. The iterative loop ends until a given threshold of the objective function is reached or a user-defined number of iterations.

By using Co-DSS methodology to transform the 3D Ip models, we are able to generate global Ip images with the same spatial pattern, as imposed, without the imposing artificial good fitness in areas of poorer seismic quality. In those areas, the final images will reflect high uncertainty (Soares et al., 2007).

In the traditional appliance of this methodology, one important but sometimes fatal assumption is made: there’s no uncertainty related with the variogram model nor the conditioning well data. The variogram model is result of an adjustment of a smooth function of a reduced number of parameters that better describe the spatial continuity of a given property.

The well data conditions the generation of the Ip models and there is no place for uncertainty related with well placement bias, measurements errors, etc.

In this thesis, we try to overcome this lack of uncertainty quantification by splitting the study area into regions and optimize the parameters related with the spatial continuity and probability distribution to better understand the impact over the retrieved models, as well as the parameters related to the regionalization of the model.

In order to understand more about GSI, the following figure schematize the proposed procedure (Fig.1):

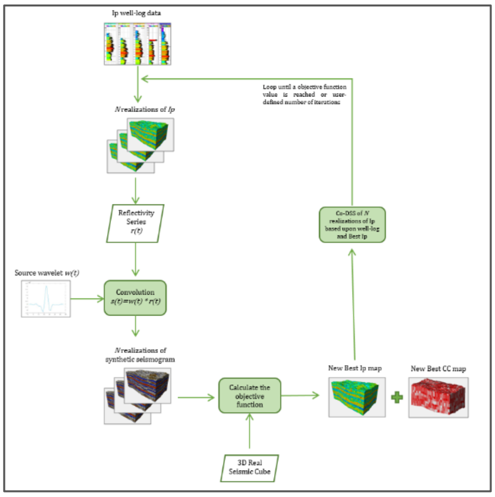

Figure 1- Global Stochastic Inversion workflow

Uncertainty Quantification

In reservoir modelling, the uncertainty quantification allows us to understand the impacts of static and/or dynamic features over the final reservoir models, and at the same time, provides the ability to take decisions with a known level of confidence.

In stochastic sequential simulation algorithms, like DSS (used in GSI), assume stationarity along the entire inversion grid (Azevedo et al.,2015), and do not take into account the uncertainty in the geological parameters referenced by the spatial continuity pattern (e.g. variogram) and in the prior probability distribution (defined by mean, standard deviation, and proportion).

In this perspective, a parameter estimation or inversion procedure is incomplete without an analysis of the uncertainty. So, these uncertainties can be explored under a Bayesian framework, and recurring to stochastic adaptive sampling algorithms.

Bayesian Theory and Particle Swarm Optimization

The Bayesian framework combines the information from the data with *a priori* information on model parameters (Duijndam, 1988). The result is *a posteriori* probability density function of the solution to the inversion problem.

The Bayes theorem (Eq. 1) allow us to determine the posterior probability taking into account the prior knowledge and can be expressed by (Mohamed et al.,2009):

$$p(m|o) = \frac{p(o|m)p(m)}{p(o)} \quad (1)$$

where, $p(m|o)$ is the posterior probability (probability of the model m given the observed data o), $p(o|m)$ is the likelihood term (probability of the data assuming the model m is true), $p(m)$ is the prior probability and $p(o)$ is a normalizing constant that suggests if the model is well adjusted to the data (the term must be small).

The likelihood term, L, can be derived from the misfit calculation, or vice versa. The misfit (Eq. 2) can be expressed as the negative logarithm of the likelihood term (Eq. 3):

$$M = -\log\big(p(o|m)\big) = -\log(L) \quad (2)$$

Or,

$$L = \exp(-M) \quad (3)$$

The misfit can be expressed in the least square sense, assuming the measurements are Gaussian, independent and identically distributed (Mohamed et al., 2009) (Eq. 4):

$$M = \sum_{t=1}^{T} \frac{(q^{obs} - q^{sim})_t^2}{2\sigma^2} \quad (4)$$

Where, T is the number of observations, q^{obs} are the observed values, q^{sim} are the simulated values and σ^2 is the variance of the observed data.

The posterior probability $p(m|o)$ can be calculated using a Neighbourhood Algorithm-Bayes (NA-Bayes) (Sambridge, 1999).

When chose to optimize the parameters, in this case referenced to the spatial continuity pattern and prior knowledge, we require a stochastic adaptive sampling algorithm to make an exploration of the parameter space, based on the misfit values.

The primary goal of these stochastic adaptive samplers is to minimize the objective function, so we can iteratively tune the simulation model parameters to match the real data and generated a set of retrieved possible models, and therefore quantify our uncertainty envelope.

In this project, we picked the *particle swarm optimization* a *“simple, fast and effective with superior global optimization compared to other stochastic algorithms*”. (Mohamed et al.,2010), which started as an algorithm to simulate social behaviour of bird communities, when flying in flock.

Then, the principles were extended to a presumable population of particles (termed swarm), placed randomly in the search space. It is assigned a random direction to each one, and when they start the movement through the search space, each particle’s direction is influenced by its previous success (low misfit achievement) and the success of the neighbours in finding regions of lower objective function (similar to bird’s quest for food).

Methodology

The main goal of this work is to assess uncertainty of key large-scale geological parameters, in parallel to the stochastic inversion procedure. The previous chapters addressed the concepts of adaptive stochastic sampling and Bayesian inference, and how these techniques allow to quantify uncertainties in model parameters.

It will be discussed the application of a particular stochastic optimization algorithm, the PSO, in regional optimization of the parameters related to the spatial continuity pattern and prior knowledge distribution about the probability distribution of the elastic properties of interest.

This thesis approaches uncertainties at different levels: locally at grid cell scale and at large scale geological uncertainty related to the distribution of the Ip and its spatial continuity pattern.

The local uncertainty is inferred by making use of stochastic simulation techniques, as in global stochastic inversion procedure, with perturbation of the model parameter space.

The large-scale uncertainty is assessed by coupling Bayesian inference and stochastic adaptive sampling based on prior uncertainty associated to the parameters that define the spatial correlation model (variogram vertical and horizontal ranges) and the ones that define the global distribution of our property of interest (mean, standard deviation and proportion of each litho-fluid facies group).

In this methodology, was also considered a set of parameters to be optimized that define the zonation of our study area into smaller sub-regions representing the uncertainty during the seismic interpretation process. Two approaches are proposed to accomplish this stochastic regionalization.

At the end we will end up with a set of parameters that defined the GMM's used to calibrate the probability distribution of Ip, a set of parameters that define the spatial distribution models (variogram ranges) and the parameters related to the zonation of the study area.

After optimization of the whole set of parameters, these will serve as inputs for the GSI algorithm that will generate a set of realizations of our petro-elastic property of interest.

Figure 2 summarizes the proposed workflow, where we distinguish the GSI loop inside the main workflow loop. At the end of the main loop, given a stop criterion (number of iteration, for example), we are ready to evaluate the uncertainty related to the retrieved models.

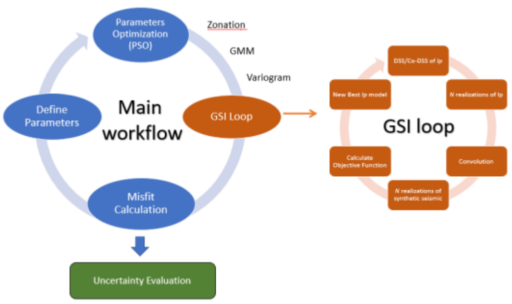

Figure 2 - Proposed workflow

Parameter Optimization

A good parametrization is a key aspect for any modelling exercise. And this case, the parametrization will allow us to assess uncertainty related to the main topics of this project: large-scale parameters (spatial distribution and global distribution) and the seismic uncertainty related to interpretation.

After several runs and comparing them to the available well-log data, the result is a set of prior ranges for each one of the parameters. Since every region has its own geological framework, we need to take this into consideration when setting the priors if we want to be geologically consistent, for variogram ranges and for probability distributions.

Variogram Perturbation

The PSO technique allows us to find the "best particle", i.e., the particle that expresses the best value for the objective function (lower misfit).

This spatial continuity pattern can be defined by a variogram model, which can be expressed by its range and direction. These parameters are normally assumed to be fixed and known. Focusing only in the models that define the vertical and horizontal directions, the PSO will tune the range of each direction, assuming a uniform distribution within a reliable range of values.

At the end, the PSO will "search" the values for each variogram range that produce lower misfit, instead of using a fixed value. Finally, the uncertainty parameters related to the variogram modelling procedure, in this case, the range of influence, can be assessed by generating multiple realizations, with different variogram model, retrieved from the available experimental data. The generation of multiple realizations allow us, also, to assess the spatial uncertainty related to the acoustic impedance, Ip.

Gaussian mixture model

Extending the concept of the workflow used in the variogram perturbation, by integrating stochastic adaptive sampling and Bayesian inference, the large-scale geological parameters, defined by the prior probability distribution, will be tuned to increase the fitness of the model.

The stationarity assumption is an intrinsic property of the stochastic simulation algorithms (Azevedo et al., 2015), leaving no space for uncertainty. The DSS algorithm states that the marginal distribution of the property to be simulated) must be reproduced like the one in the experimental data (well-log).

Yet, this distribution can be subject to uncertainty (that must be assessed), due to the preferential well placement bias (Azevedo et al., 2015), i.e., placed preferably in sand-prone lithologies (pay zones), lacking information about the rest of the study area, such as the non-pay zones.

In a way to contour this problem, Azevedo (2015) incorporated in his workflow a reconstruction of the marginal distribution (of Ip) using a Gaussian Mixture Model (GMM).

Gaussian mixture models are probabilistic models to represent a finite number of subpopulations within an overall population, In GMM we consider kernel approximations for each subpopulation, with their own mean, standard deviation and proportion (in respect to the other kernels). At the end, the result is a probability distribution which is a mixture of multiple Gaussian distributions.

A finite number of litho-fluid facies can be considered, and each one of them will be defined by its mean, standard deviation and proportion. These parameters will be optimized using the PSO algorithm and the spatial uncertainty will be assessed by generating multiple realizations of Ip. Once again, the optimization is guided by the misfit score obtained between the inverted synthetic seismogram and the real seismic.

Stochastic regionalization model

Following the work started by Nunes et al. (2016), and despite the good results, in this framework the sub-division of the study area is fixed and deterministic (one single solution) and does not reflect the uncertainty related to the seismic interpretation.

This thesis proposes to include uncertainty in the parameterization related with the boundaries at the different regions within the inversion grid.

In this case, the study area is fairly homogeneous, and it is possible to identify three main seismic stratigraphic. Thus, the geological parameters to be tuned, assuming an admissible prior interval, are the location of the lower interface of the top structure (Surface 1) and the location upper interface of the bottom structure (Surface 2), in a more simplistic point of view, the interface that delimitate the seismic unit 2. Or by optimizing a set of multipliers that subdivide these surfaces, if we consider a fixed vertical for them.

To assess the uncertainty related with seismic interpretation and seismic unit interfaces locations, we proposed two different approaches. One is to assume linearity and homogeneity of the study area and, therefore, consider interfaces parallel to the top and bottom of the area. The locations of the interfaces are optimized via PSO and the Ip model of each region is simulated (Horizontal Surface Optimization).

The second approach does not assume homogeneity of the seismic and/or interfaces. Consider a “good-fit” fixed position for the location of surface 1 and 2, we make use of multipliers to make shifts within pre-defined regions of these surfaces

Horizontal Surface optimization (approach A)

Traditional seismic inversion workflows have various ways to infer Ip models by incorporating seismic reflection data and well-log data, neglecting uncertainty at local scale. At regional scale, the seismic/geological interpretation and/or modelling techniques are anchored to a unique solution, lacking uncertainty in this process.

In this project, the aim is to evaluate the uncertainty related to seismic interpretation and assess at regional scale, by optimizing the locations of interfaces, or in other words, generating different interpretation models.

By analysing the dataset’s seismic it is possible to assume a hypothesis of a fairly linear and horizontal depositional environment. Therefore, to better distinguish the geological inconsistencies and to assess uncertainty at a small scale, we adopt a division of the original value into three seismic units.

This methodology will allow us to better handle the uncertainty related to the seismic interpretation of the three main seismic units. Thus, two new parameters are added to the list of parameters to optimize: the vertical location of the first inner surface (surface 1) and the vertical location of the second inner surface (surface 2).

First the surface’s locations are chosen around the seismic reflection lines with highest amplitude, indicating change in wave velocity, density or both. Fig. 3 shows the prior vertical locations (yellow lines for surface 1, green lines for surface 2) of the two surfaces parallel to top and bottom, under uncertainty (due to the interpretation and resolution limits of the seismic data).

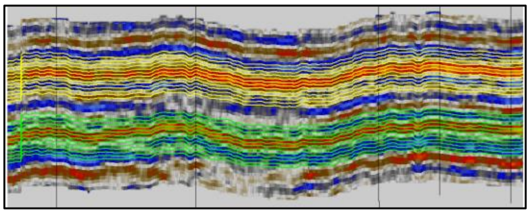

Figure 3- Possible vertical locations for both surfaces under uncertainty

Surface multipliers optimization (approach B)

On the previous approach, the first and main assumption is the linearity of the interfaces between seismic units. This assumption might be suitable for this dataset, but not the most appropriate in more heterogeneous depositional environments, especially in the presence of more complex faulting systems.

In order to test a broader approach, instead of optimizing a set of surface locations, it's considered fixed locations for both inner surfaces (maintaining the separation of the three seismic units) and added 6 new surface multipliers (3 for each surface). The comprehensiveness of each multiplier was based on an interpretation of the top surface of the dataset (Fig 4). In respect to the depth of the surface, we performed a vertical division into three sections. This sectioning it's propagated to the lower (inner) interfaces, thus each multiplier covers different section, as in Fig.4

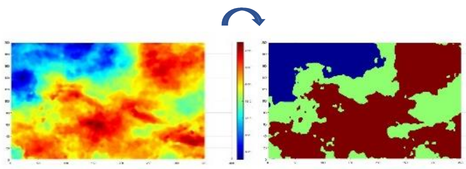

Figure 4- Top surface display (left)); Top surface sectioning into three distinct sections (blue, green and red)(right)

In a simpler way, instead of optimizing two surface locations (for three regions), we now optimize 6 multipliers, that limit 6 different regions of the grid with variable dimensions, as we can see in Fig.5:

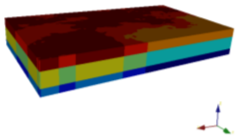

Figure 5- Sub-sectioning of the inversion grid, one for each multiplier

At the end, we end up with 39+6 parameters to optimize

Parametrization

The proposed workflow ran with 500 iterations, with 5 realizations each, using Direct Sequential Simulation, for Ip model generation, and adaptive stochastic sampling and Bayesian inference algorithms to tune the large-scale parameters. At the end, we end up with a total of 2500 Ip models.

For analysis and comparison purposes, in addition to the Ip models, we also have as output of this workflow, 500 "best" correlation coefficients models, 500 "best" acoustic impedance models (one per iteration) and 2500 inversed synthetic seismograms.

We can use many different stop criteria, but in this case, the stop criterion is a user-defined number of iterations (in this case, 500 iterations).

Until this moment, excluding the parameters for the regionalization, but considering a subdivision of the area into three regions, we end up with a sum of 39 parameters.

Results and Discussion

The Fig. 6 and 7 presents the evolution of this trace-by-trace mismatch for both approaches, that clearly shows a decrease of the misfit and indicating a convergence of the inversion procedure. This behaviour is intrinsic of the used adaptive stochastic sampler (PSO).

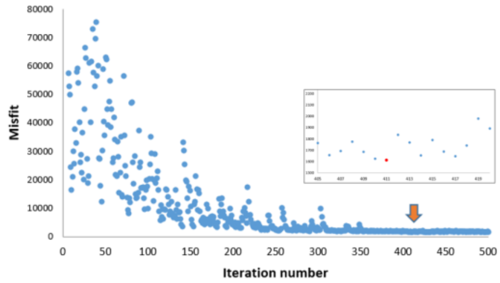

Figure 6- - Misfit evolution throughout the iterative process (approach A), pointing out the iteration with lowest misfit (it. 411)

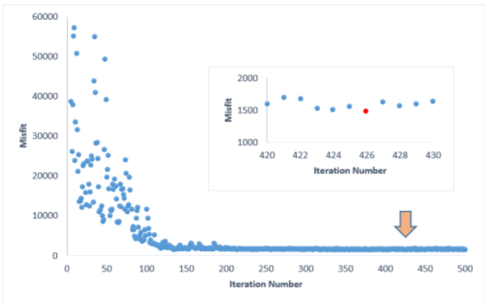

Figure 7- Misfit evolution throughout the iterative process (approach B), pointing out the iteration with lowest misfit (it. 426)

The iterative process of approach B seems to reach convergence sooner and the misfit score is lower (M=1476.3913) at iteration 426, against the one on approach A (M=1614.47) at iteration 411.

If we assess the evolution of each parameter individually through the PSO sampling (Fig. 8, as an example), the result shows a clear convergence without compromising the exploration of the parameter space, therefore the range of values for each parameter that generated models with a given misfit score below a certain threshold, represent a plausible uncertainty space related to each variable. If, for every iteration, face the parameter value with the correspondent misfit score, we can see which value(s) produce lower misfit.

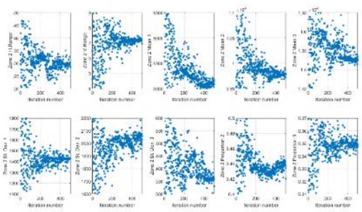

Figure 8- Parameter evolution throughout the iterative procedure (single region)

Throughout the iterative process (for both approaches), the synthetic seismic is getting closer to the real data, shorten the range of the solutions. An example of a single trace picked in a random location in the grid, and for an interval of 50/100 iterations (between 1-50, 100-200,200-300,300-400,400-500), Fig.9 shows the maximum and minimum value of range of solutions generated at each interval:

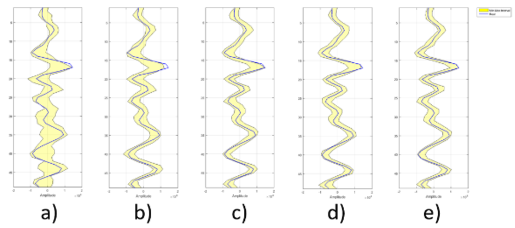

Figure 9- Min-max interval around the real seismic trace (blue line); a) Iterations 1-50; b) Iterations 100-200; c) Iterations 200-300; d) Iterations 300-400; e) Iterations 400-500

Thus, in Fig. 9 there's a clear convergence of the solution to a better fit one, shortening the range of solutions along the iterative process. In the first stages of this process, the algorithm shows more explorative and gives a set of many different scenarios, but soon it becomes more exploitative and trying to get closer to a low misfit solution.

In approach A, when analysing the distribution of the variable of interest, Acoustic Impedance (*Ip*), in Fig. 10, it is clear the good match between the simulated grid and the non-conditioning well-data (blind test). The surface 1 and 2 locations are in accordance with the main seismic units and delimit properly the change in geology, in terms of the properties that affect the *Ip* (p-wave velocity and density).

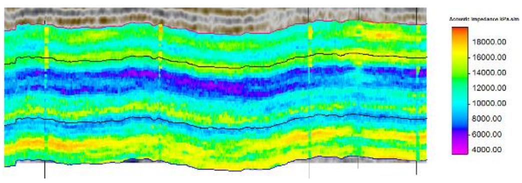

Figure 10- Vertical well section from an Ip model (Iteration 411)

Is also important to find which set of possible vertical locations of the region's surfaces lower the overall misfit score, in other words, which is the space of uncertainty at the end of the iterative scheme. Fig. 11 illustrates the set of values versus the overall misfit scores.

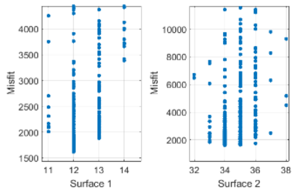

Figure 11- Vertical surface locations versus Misfit Score

Thus, taking the values of 11,12 and 13 as the values with lower misfit for surface 1 and 33,34,35 and 36 for surface 2, and plot those in the seismic data (Fig. 12), it is possible to acknowledge that the uncertainty related to these locations is reduced to half of the wavelength of the seismic reflection, in other words, close to the theoretical vertical resolution of the real seismic reflection data.

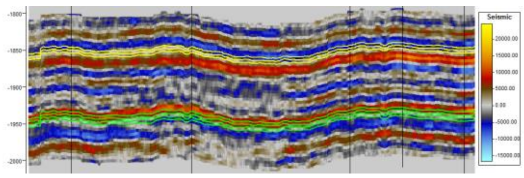

Figure 12- Vertical well section the surface's location with lowest misfit.

In approach B, we can easily notice a clear path to a solution very close to the real distribution of *Ip*. These models, at latest stages of the iterative process, show a clear match with the non-conditioning hard-data (blind test), even for far apart wells. The heterogenous models converge into very linear and homogeneous, in accordance to the geological background, very similar to the seismic distribution.

For the best-fitted model, at iteration 426, both *Ip* model (Fig.13) seem to be tuned with the previously seen iterations. In terms of blind test, Fig. 13, the generated *Ip* model is in respect to the non-conditioning wells.

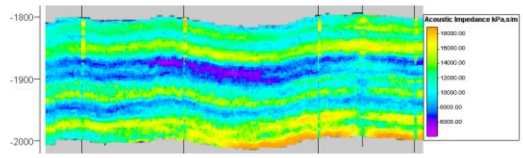

Figure 13- Vertical well section from an Ip model (iteration 426)

In Fig.14, we have a perception of the set of values that produce lower misfit scores. For most multipliers, the value associated to models with lower misfits is not zero. This observation shows us that the theory of linear surfaces probably it is not the best-fitted one, since surfaces with different shifts in depth produce models with lower misfit.

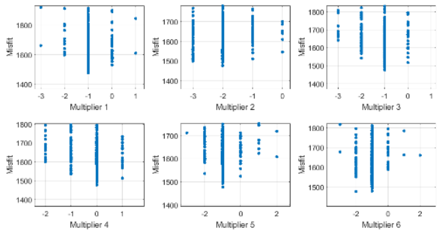

Figure 14- Misfit scores for optimized multipliers values

Finally, comparing the results of *Ip* models generated in both proposed approaches with one *Ip* model (Fig. 15) generated by GSI, without incorporation of any optimization, it is easy to see some difference in the retrieved results, especially related with the bounds of *Ip* strongly conditioned by the well-data, which demonstrates the lack of uncertainty related with the large-scale parameters that define the spatial continuity model and global distribution of the acoustic impedance.

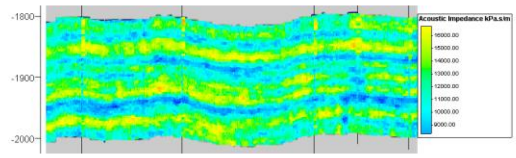

Figure 15 - Retrieved Ip model from GSI algorithm

Conclusions

Seismic interpretation is crucial in any E&P project, yet immersed in an enormous amount of uncertainty, related to the geologist point of view. During decision making, this uncertainty might be important to avoid taking severe risks that can compromise the whole project.

Reason why, the main motivation for this project was to assess the larger amount of uncertainty possible related to the seismic interpretation process. Since this methodology involves the use of geostatistical seismic inversion methodologies, these are plagued with uncertainty too, due to the nature of inversion problems.

By coupling Bayesian inference and stochastic adaptive sampling (PSO), it was possible to assess the uncertainty related to the large-scale parameters. And for each approach quantify the uncertainty related to the seismic interpretation: regionalization model interfaces.

Both approaches shown good results, especially in the retrieved models of the property of interest: acoustic impedance (*Ip*), showing very good results in the blind tests, however, it shown that assuming linearity of the dataset might not be so easy, and that this can compromise the results, since the use of multipliers, in this case, shown better results in terms of misfit.

In the first approach (Horizontal Surface optimization), despite the good results, and the easy implementation, is important to highlight the search for a good context of application, i.e., we must be sure of the homogeneousness of the dataset.

The second approach, might be better for fractured/heterogenous environments, as mentioned before, because it can have a clearer overview of the uncertainty related to shifts in the interfaces, therefore in the seismic interpretation.

This whole methodology allowed us to make an integrated quantification of local, regional and global uncertainty, and to better understand the different set of possible scenarios for regionalized models. And its success might be the beginning for different studies, different datasets, different zonations, towards a better understanding of the underground geological framework.

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