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A family of particle swarm optimizers for reservoir characterization and seismic history matching.

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Summary

One of the major challenges in reservoir modeling for optimizing production is characterizing the spatial distribution of heterogeneous reservoir properties – facies, porosity, and permeability. Time-lapse seismic data in combination with geological and flow modeling has evolved as an important diagnostic tool for efficient reservoir characterization. However, joint inversion of seismic and flow data for reservoir parameters is a highly non-linear and complex problem. In recent years, with the great increase in computer power, stochastic optimization has shown good results in tackling these data integration problems. One of the more recent stochastic optimization methods is particle swarm optimization (PSO). We describe a family of particle swarm optimizers and apply different particle swarm optimizers (PSO) to a seismic history matching problem. The algorithms are first tested on a 2-D synthetic sand-and-shale reservoir section, and then applied to the 3-D real data set from the Norne field in the North Sea. The ill-posed character of this inverse problem is attenuated by reducing the model complexity using a Spatial Principal Component base and by combining as observables flow production measurements and seismic data. Additionally the inverse problem is solved in a stochastic framework searching for the family of reservoir models that equally fit the data. We show that PSO algorithms have a very good convergence rate and in addition provide approximate measures of uncertainty around the optimum facies model. The uncertainty estimation, although it is a proxy for the true posterior distribution of model parameters, allow us to perform risk analysis.

Introduction

Characterizing the spatial distribution of heterogeneous reservoir properties is one of the major challenges in reservoir modeling for optimizing production. Well data together with seismic data are typically used to infer the spatial distribution of properties such as facies, porosity and permeability. The seismic history matching problem consists then in obtaining reservoir models that match production data as well as seismic time lapse data. The main challenge of this inverse problem is that the production data alone does not uniquely constrain the porosity and permeability of the reservoir. Combining flow production measurements with time lapse seismic data has been useful for better constraining the history matching(Huang et al., 1997; Echeverría and Mukerji, 2009; Xia and Huang, 2009; among others). Furthermore, to run the flow simulator and produce accurate results a detailed description of the reservoir is needed. This causes the inversion problem to be highly ill-posed due to its underdetermined character. One solution commonly found in the literature is to use non-linear least-squares methods with Tikhonov regularization around a reservoir reference model that is constructed using prior geological and geophysical knowledge. The result is a unique reservoir model that shows the best trade-off between the data prediction and the model complexity. No uncertainty estimation is usually performed around this model due to the high computational cost. In addition, the validity of the uncertainty analysis is limited by the highly non-linear character of the history matching inverse problem. Moreover, local methods for non-linear problems are highly dependent on the initial guess. This feature hampers their robustness.

Stochastic approaches to inverse problems consist in shifting attention to the probability of existence of certain

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interesting subsurface structures instead of looking for a unique model. Global optimization methods are well suited to perform this task. Although global algorithms can be used in exploitative form, their main advantage is that they can potentially address the inverse problem as a sampling problem. Their use as samplers requires a reasonably fast forward modeling and a small number of independent parameters. The use of Particle Swarm Optimization in geosciences still remains restrained (Shaw and Srivastava, 2007; Fernández-Martínez et al., 2010 a,b). In reservoir engineering PSO has been used to determine the optimum well location and type in very heterogeneous reservoirs (Onwunalu and Durlofsky, 2009). The use of global optimization techniques is hampered in real history matching problems by the large number of parameters needed to accurately describe the reservoir and by the very costly forward solutions. The second problem can be solved using faster approximations of the forward problem and running the forward simulation in parallel. The first issue is addressed by reducing the dimensionality of the model space (see for instance Echeverría and Mukerji, 2009; Romary, 2009). In this paper we use the same reduction technique (spatial principal component analysis) that has been used in Echeverría and Mukerji (2009) but use the PSO family as global optimizer. We show that the combined use of particle swarm algorithms and spatial principal component analysis allows solving the seismic history matching problem in a geologically consistent way, and to provide a proxy for facies uncertainty.

Methodology

Let the model parameters $\mathbf{m} \in \mathbf{M}$ be the set of reservoir models formulated in terms of geological consistency. The model $\mathbf{m}$ can be an indicator random variable (facies), or a Continuous random variable representing porosity associated with every grid block in the reservoir simulator; $\mathbf{d} \in \mathbf{R}^m$ is the observed data comprising all the observables, e.g. production and/or seismic data and $\mathbf{F}(\mathbf{m})$ symbolizes all the forward models needed to compute the data: a reservoir flow simulator to predict the production data, a forward seismic model, a geostatistical model to constrain the spatial structure of the reservoir, and also the rock physics model to compute porosity-permeability relations for each facies and the rock physics models to compute changes in Vp, Vs, and density due to production- related changes in pore fluid saturations. In our stochastic framework we are interested in sampling the family of models that fit the data within a certain tolerance $\| \mathbf{F}(\mathbf{m}) - \mathbf{d} \|_p < tol$ in order to be able to compute uncertainty on the reservoir facies. The methodology includes the following steps:

1. Dimensionality reduction and regularization using the spatial principal component base. This reduction allows us to perform sampling on the reduced model space using the particle swarm optimizers in this case.

2. Sampling using the different members of the PSO family. Their convergence is related to the first and second order stability of the particle trajectories. In this paper we use a cloud version for the PSO optimizers (Fernández- Martínez and García-Gonzalo, 2009, 2010).

3. Posterior analysis to estimate the posterior distribution of the model parameters from the samples gathered on the low misfit region. Based on the PSO samples we can get statistical expectations (E-type) of the facies models and a measure of the uncertainty of these facies in each cell of the reservoir (the inter-quartile range for example).

Parameter reduction: the PCA spatial base

Principal component analysis is a well-known mathematical procedure that transforms a number of correlated variables into uncorrelated variables called principal components. The transformation is such that the first principal component accounts for as much of the variability and each succeeding component accounts for as much of the remaining variability as possible (Jolliffe, 2002). Usually PCA is performed in the data space, but in this case it is used to reduce the dimensionality of the model space based on a priori samples obtained from conditional geostatistical realizations that have been constrained to static data. The method works as follows:

1. First we generate an ensemble of plausible reservoirs using multipoint geostatistics (Strebelle, 2002). We had 1000 different reservoir realizations all

conditioned to static well data.

2. The reduced PCA base $\mathbf{V} = \{\mathbf{v}_1, \mathbf{v}_2, \ldots, \mathbf{v}_d\}$ comes from diagonalizing the ensemble centered covariance and selecting the first d (~30 to 60) PCA terms ($d \ll N$) to match most of the variability in the model ensemble. Then, any reservoir model in the reduced space is represented as a unique linear combination of the eigenmodels,
$\hat{\mathbf{m}}_k = \boldsymbol{\mu} + \sum_{i=1}^{d} a_i \mathbf{v}_i,$ where μ is the model experimental mean.

3. The search is finally done on the a_i coefficients. The orthonormal character of the vectors $\mathbf{v}_i$ provides to this base a nested character; that is, if we add the next eigenvector $\mathbf{V}_{d+1}$ to the base, the vector $\hat{\mathbf{m}}_k - \boldsymbol{\mu}$ will be expressed in these two bases as follows:
$$\hat{\mathbf{m}}_k - \boldsymbol{\mu} = (a_1, \ldots, a_d)_{\{\mathbf{v}_1, \ldots, \mathbf{v}_d\}} = (a_1, \ldots, a_d, 0)_{\{\mathbf{v}_1, \ldots, \mathbf{v}_d, \mathbf{v}_{d+1}\}}.$$
This property allows an easy implementation of a multi-scale inversion approach adding more eigenvalues to match finer scales of heterogeneity as needed. All the finer scales might not be informed by the observables, that is, they might belong to the null space of our local linear forward operator. By truncating the number of PCA terms that we use in the expansion we are setting these finer scales to zero avoiding also the risk of over fitting the data.

The Particle Swarm Optimizers

Particle swarm optimization is a stochastic evolutionary computation technique (Kennedy and Eberhart, 1995) used in optimization, which is inspired by social behaviour of individuals (called particles) in nature such as bird flocking and fish schooling. The algorithm has been described in many publications, but we give the main equations below for completeness. Each particle (model) has its own position in the search space. The particle velocity represents the parameter perturbations needed for these particles to move around in the search space and explore solutions of the inverse problem. At each iteration the algorithm updates the positions, $\mathbf{x}_i(k)$ and the velocities, $\mathbf{v}_i(k)$ of each particle in the swarm as follows:

$$\mathbf{v}_i(k+1) = \omega \mathbf{v}_i(k) + \phi_1(\mathbf{g}(k) - \mathbf{x}_i(k)) + \phi_2(\mathbf{l}_i^k - \mathbf{x}_i(k))$$
$$\mathbf{x}_i(k+1) = \mathbf{x}_i(k) + \mathbf{v}_i(k+1),$$
$$\phi_1 = r_1 a_g, \quad \phi_2 = r_2 a_l, \quad r_1, r_2 \in U(0,1), \quad \omega, a_g, a_l \in \mathbf{R},$$

where ω is called inertia, a_g, a_l are the global and local acceleration constants, $\mathbf{l}_i(k)$ the particle's best position found so far (called, the local best), $\mathbf{g}(k)$ the particle with lower misfit found thus far in the entire swarm (called the global best), and r_1, r_2 are vectors of random numbers uniformly distributed in (0,1), to weight the global and local acceleration constants $\bar{\phi} = \frac{a_g + a_l}{2}$ is the total mean acceleration and plays an important role on the algorithm's stability and convergence (Fernández-Martínez et al., 2008a). The PSO algorithm can be physically interpreted as a particular discretization of a stochastic damped mass- spring system (Fernández-Martínez and García-Gonzalo, 2008). Based on this stochastic differential model a whole family of PSO algorithms (Fernández-Martínez and García- Gonzalo, 2009) have been derived by considering various differencing schemes, centered difference, backward difference, and forward difference for the velocity and position updates: (1) Generalized GPSO or centered-regressive PSO, (2) centered-centered (CC-PSO), (3) centered-progressive (CP-PSO), (4) progressive-progressive (PP-PSO) and (5) regressive-regressive (RR-PSO). Although these algorithms are stochastic in nature they are not heuristic, since their convergence can be related to the first and second order stability of the trajectories now represented as stochastic processes (Fernández-Martínez and García-Gonzalo, 2008; 2009).

The stability regions can be defined in the space of $\omega - \bar{\phi}$. The first and second-order spectral properties of different variants in the algorithm family determine the explorative capabilities of the swarm. CP-GPSO has greater exploration capabilities than the GPSO and CC-PSO due to its first and second order spectral properties (Fernández- Martínez and García-Gonzalo, 2009). This fact has also been found in practice in the solution and appraisal of inverse problems (Fernández-Martínez et al., 2008b, 2010 a,b). Good parameter sets are close to the upper boundary of the second order stability region where the action of the cost function attractors is weak. Above this line we achieve a very explorative behavior (Fernández-Martínez and García-Gonzalo, 2009). Based on these results we have designed for each PSO version a cloud-PSO algorithm where each particle of the swarm has associated a different (ω, a_g, a_l) set located on this region, instead of the more common algorithm where every particle has the same set of parameters (Fernández Martínez et al, 2010). The cloud design allows the different swarm members to find the sets of parameters that are better suited for solving each inverse problem. Some particles will have a more exploratory behavior while others will show a higher exploitative character. Also, in the algorithm design the time step parameter (Δt) plays a very important role: increasing it provides more exploratory character and allows escaping entrapment in local minima, while decreasing it $(\Delta t < 1)$ allows for a more detailed local search around the global best (Fernández-Martínez and García-Gonzalo, 2008).

Norne Field

The Norne field is located in the blocks 6608/10 and 6508/10 on a horst block in the southern part of the Nordland II area in the Norwegian Sea. The rocks within the Norne reservoir are of Late Triassic to Middle Jurassic age. The present geological model consists of five reservoir zones. They are Garn, Not, Ile, Tofte and Tilje. Oil is mainly found in the Ile and Tofte Formations, and gas in the Garn formation. The sandstones are buried at a depth of 2500-2700 m. The porosity is in the range of 25-30 % while permeability varies from 20 to 2500 mD (Steffensen and Karstad, 1995; Osdal et al., 2006). The data consist of near, mid and far stack 3D seismic data acquired in 2001, 2003, 2004 and 2006. Given the high volume of data set, at first we apply the method on a 2-D section of segment E of Norne field (Figure 1) to test the workflow. Then it is applied to the 3-D segment E of Norne field. The 2-D model has 1014 grid block (39 x 1 x 26) (Figures 2 and 3) with one injector and one producer at column 6 and 36 respectively. The properties of these wells are similar to the well F-4H in the Norne field. The grid sizes vary from 2-20 m in vertical direction and from 80-100 m in horizontal direction.

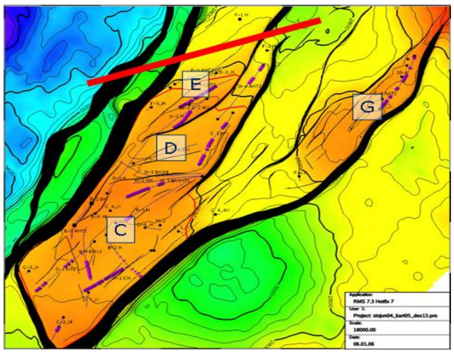

Figure 1: Top view of Norne field showing segment E and 2D section used in this study.

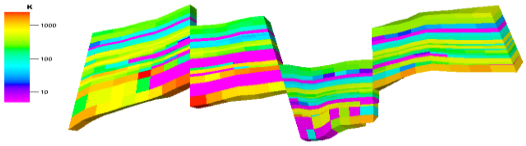
Figure 2: Permeability distribution of 2D synthetic section of Norne field.

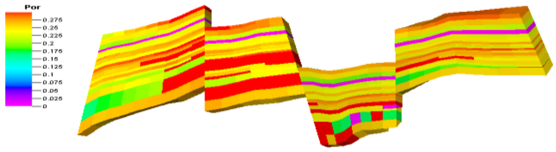
Figure 3: Porosity distribution of 2D synthetic section of Norne field.

Results on 2D section

One thousand geostatistical realizations of porosity field are generated using sequential Gaussian simulation conditioned to the well data and variograms. Corresponding permeability fields are generated based on the relationship between porosity and permeability in different zones. All of the versions of PSO provide an acceptable match with the original synthetic model (Figure 4 and Table 1). The advantage of using global optimization method is that variability of the models can be assessed near the optimum point. This is shown by plot the best, the E-type (ensemble average) and IQR (Inter quartile range) of porosity and permeability for each version of PSO (Figure 5).

Algorithm	Misfit
CC	0.1169
CP	0.1448
PP	0.1209
PSO	0.2383
RR	0.0933

Table 1: Value of misfit in different PSO algorithms

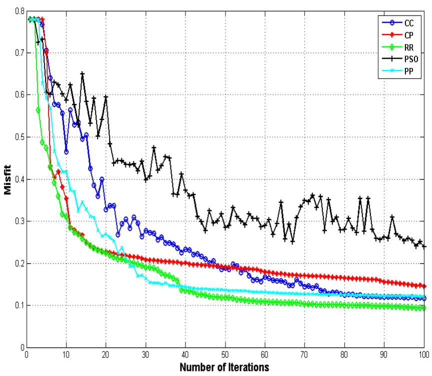

Figure 4: Behaviour of objective function for 100 iterations

Extension to 3-d

After having tested the algorithms and workflow on the 2-d section we extend this to full 3-d considering the E segment of the Norne field. We created one thousand geostatistical realizations of reservoir models for segment E of Norne field (Figure 5 shows one realization). The reservoir models are created based on the well log data using SGSIM (sequential Gaussian simulation). These one thousand realizations are used to perform spatial PCA and get the reduced base by selecting seventy major principal components Rock physics models are generated for segment E based on the well log data available for each reservoir zone (Figure 7). These models are developed for four different regions in each of the reservoir zones.

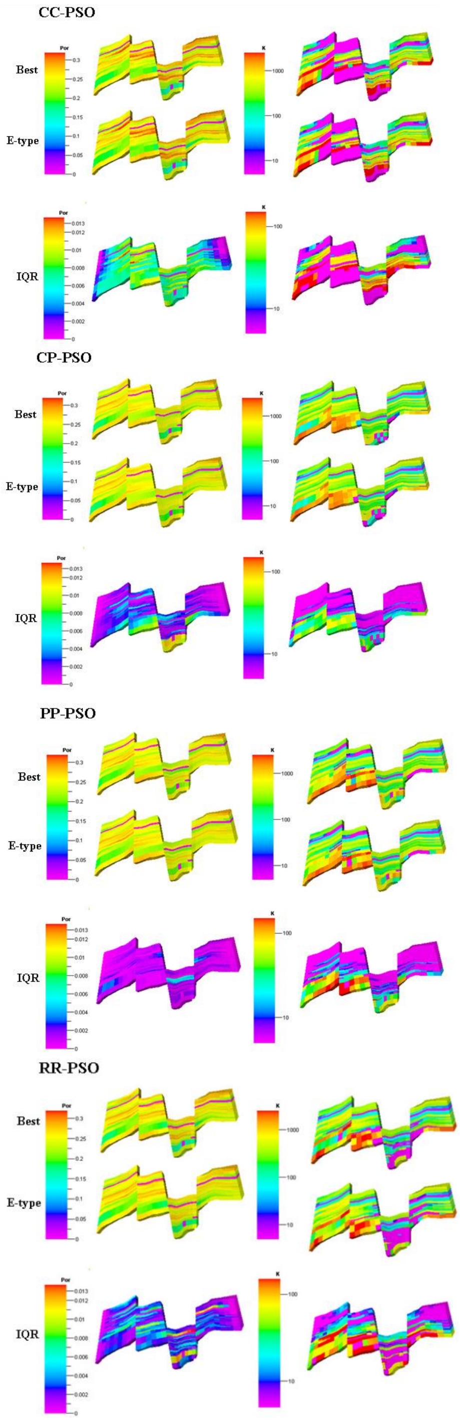

Figure 5: Variability around optimal model for different PSO algorithms; (left column: porosity; right column: permeability).

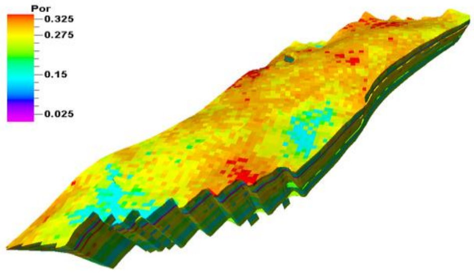

Figure 6: Realization for segment E generated using well log data

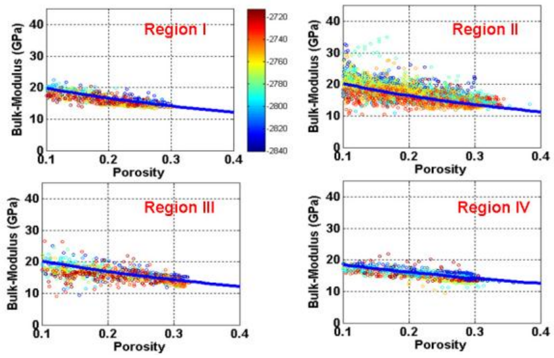

Figure 7: Rock physics models for different zones of Norne field

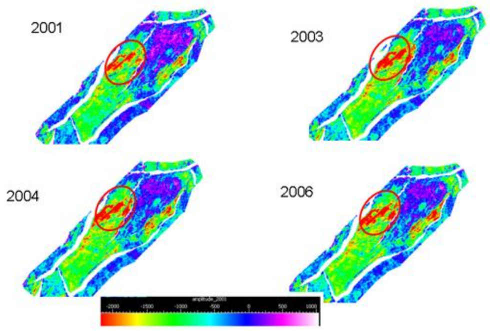

Figure 8: Seismic amplitude at the top of Garn at different years

Near offset seismic amplitudes are mapped on the top of Garn formation at different times (Figure 8). The changes in the seismic amplitude at this horizon will be considered as observed seismic data to constrain the updates of the reservoir model. The objective function consists of sum of misfit of production and seismic data. The production data misfit consists of normalized L2 norm of difference between modeled and observed production data. The seismic data misfit is the difference between relative root mean square amplitude change on top of segment E between 2001 and 2004 in the observed and modeled seismic data.

Figure 9 shows the production response of observed and best history matched model. We obtained a very reasonable history match for all the wells except E-3AH. The relative root mean square amplitude change on top of segment E between 2001 and 2004 for the best history matched model is 9.1 (reasonably close to that of observed seismic data i.e. 10.7). Figure 10 compares the best history matched model with the provided smooth initial model, showing much more heterogeneity reservoir properties.

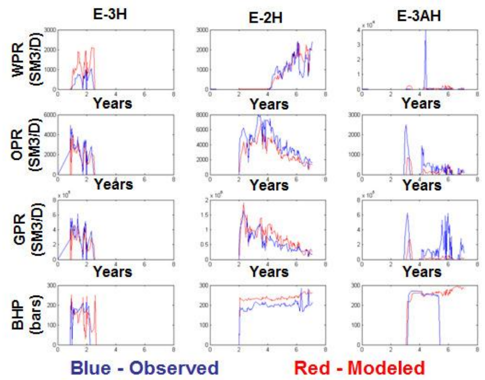

Figure 9: Comparison of production response of best history matched model and observed data

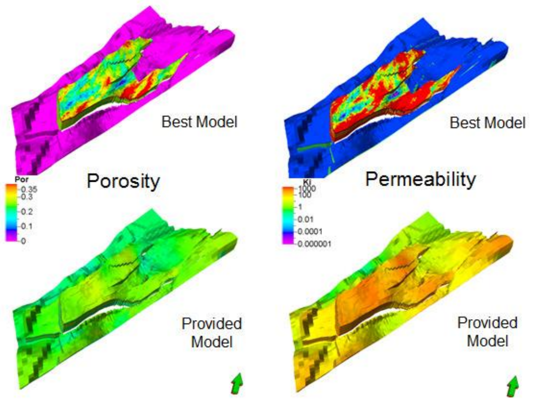

Figure 10: Porosity and permeability distribution of best history matched model.

Conclusions

We have shown for the synthetic 2-D and the real 3-D Norne data that the combined use of particle swarm algorithms and model reduction techniques such as principal component analysis allows solving stochastically the seismic history matching problem and to provide a proxy for facies uncertainty. The family of plausible reservoir models is partially constrained by the use of time lapse seismic, and production data, in addition to calibrated rock physics models and geostatistics.

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