A multi-objective stochastic optimization approach for estimation of subsurface geomodels

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SUMMARY

We present a multi-objective optimization approach to the subsurface geomodel updating problem using stochastic search techniques. This is a new approach to the geomodeling process for which a variety of direct and indirect measurements can simultaneously constrain the geomodel. Due to the inherent uncertainties and noise in real data measurements, geological and geophysical datasets acquired in the same area may be in conflict with each other and a realistic subsurface model can only be obtained by simultaneously integrating the combined datasets in a reasonable manner. One approach to this problem is to perform joint inversion of multiple geological and/or geophysical datasets, where an optimal model is achieved by optimization of a linear combination of several objective functions measuring the match of the simulated datasets with the observed datasets. In this paper, we consider joint inversion of multiple datasets for geomodel updating, as a Multi-Objective Optimization Problem (MOOP), where separate objective functions for each subset of the observed data are defined. Then, a stochastic optimization technique is employed to find the set of best-compromise model solutions that fit the defined objectives along the Pareto front. We demonstrate that a customized initialization of the algorithm can speed up the convergence and result in a set of improved model solutions. We apply the proposed approach on a 3D reservoir litho-facies model that must honour a set of geological and geophysical attributes (e.g. log data and inverted seismic P- and S-wave impedances).

Key words: multi-objective optimization, reservoir geomodel updating, seismic impedances

INTRODUCTION

Subsurface modelling is a fundamental practice in most disciplines of Earth science like hydrology and ground water analyses, geothermal studies, coal and mineral exploration, oil and gas reservoir modeling, petroleum system analysis and CO2 geosequestration. Yet construction of physically plausible subsurface models based on the data measured at the earth’s surface or at drilled locations continues to present a number of challenges for researchers and technologists.

To accurately model the subsurface conditions in three dimensions, a variety of geological data (e.g. core measurements, well logs and sedimentological maps) and geophysical measurements (e.g. seismic, EM and gravity) are required. However, even the most sophisticated algorithms sometimes fail to produce convincing results, since each of these information sources have limitations. We believe that a realistic subsurface model can only be obtained by reconciliation of several kinds of such measurements. For instance, while geological data can provide the general distribution of subsurface model properties, other factors like limited lateral coverage of wells and the associated heterogeneities of the majority of the properties, may lead to highly uncertain models (Saussus and Sams, 2011). In this context, geophysical data, due to its high spatial coverage, could add new information not only to the definition of the model framework and geometry, but also to the discrete and continuous property modeling process (Emami Niri and Lumley, 2013). Promising results can be achieved if the final models simultaneously honour several objectives with respect to each of the integrated datasets. The nature of subsurface modeling therefore can be seen as a nonlinear optimization problem with multiple goals.

Conventionally, there are two broad approaches to handle the multi-purpose subsurface geomodeling process (Kozlovskaya et al., 2007):

1- Independent inversion of each dataset to obtain different self-directed models. In such a procedure, the final model is produced by the combination and correlation of the separate models.

2- Joint inversion of multiple datasets which directly results in the final model.

A common approach for the joint inversion of multiple datasets is the weighted summation of the defined fitness functions for each set of the integrated datasets to obtain a global objective function. This objective function is then optimized using a classical inversion technique to find the best fitting model. However, this would be subject to user bias. In this study, we demonstrate that such a joint inversion problem for the subsurface geomodeling process can be tackled as a Multi-Objective (MO) Optimization Problem (MOOP). Our proposed approach consists of two sequential steps. First, all relevant problem domain knowledge and prior information should be integrated in order to generate several possible models. Second, a MOOP should to be designed to update the model in such a way that, for several sets of the observed data, multiple objective functions are defined. Then, we use a population-based stochastic search technique to find the best compromise model solutions among all components of the objective function vector (found along the Pareto front) in a single simulation run.

This paper is structured as follows. First, we introduce the basic concepts of MOOPs and the proposed MO inversion approach for the geomodel estimation, followed by its application to a 3D synthetic case study. We then present the
qualitative and quantitative analyses of the results and summarise the conclusions of this study.

MULTI-OBJECTIVE OPTIMIZATION

The general form of a MOOP can be written as follows. Note that here opt means the optimum (minimum or maximum) of a vector objective function.

\[
\hat{f}(\bar{x}^*) = \underset{\bar{x} \in \mathcal{F}}{\text{opt}} \hat{f}(\bar{x})
\]

Where \( \hat{f}: \mathcal{F} \rightarrow \mathbb{R}^k \) (Eq.1)

and \( \mathcal{F} = \{ \bar{x} \in \mathbb{R}^n | \bar{g}(\bar{x}) \geq 0, \bar{h}(\bar{x}) = 0 \} \) (Eq.2)

These equations indicate that a MOOP can be defined as finding a vector of decision variables \( \bar{x}^* = [x_1, x_2, ..., x_n]^T \) which optimize a vector of objective functions \( f_i: \mathbb{R}^n \rightarrow \mathbb{R} \) \( \bar{f}(\bar{x}) = [f_1(x), f_2(x), ..., f_k(x)]^T \) subject to \( p \) equality constraints of \( h_i(x) = 0, i = 1,2, ..., p \), and the \( m \) inequality constraints of \( g_i(x) \geq 0, i = 1,2, ..., m \), where \( n \) is the number of decision variables and \( k \) is the number of the objective functions. The restriction imposed by the constraints defines the feasible region within the search space \( (\mathcal{F} \subseteq \mathbb{R}) \), and any \( x \in \mathcal{F} \) yields a feasible solution. The vector \( \bar{f}(\bar{x}) \) gives the optimal solution and normally there is more than one optimal solution (Singh et al., 2008).

The concept of optimality in MOOPs differs from the Single Objective Optimization Problems (SOOPs). Actually, determining an optimum solution (\( \bar{x}^* \)) for a MOOP is an ideal situation that rarely occurs in real cases (Figure 1). So, it is necessary to consider what an optimal solution means in such cases. In fact, rather than searching for a single optimum, it may be more appropriate to search for a set of optimal solutions which means the best compromises or ‘trade-offs’ among all feasible solutions for the defined objectives (Coello et al., 2002).

The application of the proposed MO model updating approach for the simultaneous integration of various datasets in the subsurface geomodeling procedure is presented using a 3D synthetic case study to show the different steps of the proposed approach and testify its validity. In addition, the sensitivity of the model solutions to changes in the optimization algorithm parameters and the presence of seismic noise are analysed.

In this synthetic case study, we prefer to work at the seismic scale. First, we synthetise a base reservoir lithology model, consisting of 55% sand and 45% shaly sand (Figure 2a) and then calculate the P-wave and S-wave impedance volumes (Figure 2b) for the reference litho-facies model, using a PetroElastic Model designed based on theoretical and experimental relationships. The 3D model contains 12 x 12 x 10 grid blocks (total 1440) with dimensions 12.5x12.5x7 m³.

The unknown property for the inversion could be any of the discrete or continuous reservoir petrophysical properties. In this study, we concentrate on deriving the correct facies models, meaning that the unknown reservoir property at the continuous or discrete reservoir petrophysical properties.
optimization loop is the facies indicator at each grid block of the 3D model framework.

Figure 2: (a) Reference Litho-facies model and pseudo-wells and (b) reference P-wave impedance cube

For a correct and efficient automatic updating of the subsurface models, the choice of fitness functions is vital. In this study, we define two objective functions to construct the seismically-consistent litho-facies models. They account for the mismatch between the synthetic P- and S-wave impedance cubes (Ip and Is) of the models and the reference (observed) Ip and Is cubes. Here, the forward modeling operator is the facies-dependent petroelastic model defined to convert the reservoir model parameters to the elastic attributes. In the proposed reservoir approach, at each generation and for every single model in the population, the Ip and Is response of the 3D model is predicted based on the petroelastic model.

SENSITIVITY ANALYSIS

We quantitatively evaluate the sensitivity of the model inversion results in response to changes in the optimization algorithm’s parameters by computing the corresponding average misfit error for each set of the facies models. The sensitivity analysis results confirm that in our proposed approach for subsurface model updating, integration of problem-specific knowledge into the generation of the initial population may accelerate convergence resulting in better solutions. In particular, incorporating seismic data into the facies modeling process (Emami Niri and Lumley 2013) could significantly improve the performance of the proposed MO inversion approach.

RESULTS AND DISCUSSION

Once the objective functions were defined and the optimum MOEA’s parameters (population size, initial population members and cross-over and mutation fractions) were obtained, the proposed MO inversion was performed. Figure 3 shows the solutions move towards the Pareto optimal set in the objective function space during successive generations. In MOOPs, the number of objective functions is usually considerably less than the number of model parameters. Therefore, plotting solutions in the objective function space, instead of the model space, is a useful tool for quality control of the model solutions. This feature of MOOP adds an efficient attribute to our proposed geomodel updating process by allowing for the evaluation of accuracy, non-uniqueness and uncertainty of the results.

The misfit errors of the initial models were 25-36.5%. This mismatch rate reduced to 14.6-18.9% after 90 generations of the proposed approach. The search process stopped at this point because no more enhancements in the objective functions were possible. Figure 4 shows a realization of the final set of models after the MO geomodel updating process. This figure also shows the reference geomodel and a realization of the initial models in order to emphasize the improvements in the final model. It is clearly shown that there is an acceptable visual match between the true reference model and the model obtained by the proposed approach.

In the final step of this study, we tested the sensitivity of the proposed inversion approach to the following noise options in order to investigate the robustness of the approach to the presence of noise in the observed data:

- **Noise1**: Error in petroelastic model
- **Noise2**: Error in petroelastic model plus 20% band-limited noise in the seismic data
- **Noise3**: Error in petroelastic model plus noise due to low vertical resolution of seismic data

The results of the noise sensitivity tests are expressed in terms of the confidence matrix (Table 1) to quantify the performance of the inversion respect to the different varying noise options. In fact, the diagonal elements of this matrix indicate what percentage of the each facies is correctly reconstructed by the proposed inversion algorithm (Grana et al., 2012). We can see from the table that for Noise1, 78 and 89 percent of sand and shaly sand is correctly estimated, whereas the percentage of the correct prediction fell to 75 and 86 in Noise2 and 74 and 83 in Noise3 respectively. It is clear that although presence of different kinds of noise in the seismic data slightly reduces the robustness of the presented inversion procedure, the obtained model solutions are still reliable.

<table>
<thead>
<tr>
<th>Table 1: Confidence matrix after MO inversion (Ref stands for reference and Sim stands for simulated)</th>
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<tr>
<td>Ref-Sand</td>
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<tr>
<td>Noise1:</td>
</tr>
<tr>
<td>Ref-Sand</td>
</tr>
<tr>
<td>Ref-Shaly Sand</td>
</tr>
<tr>
<td>Noise2:</td>
</tr>
<tr>
<td>Ref-Sand</td>
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<tr>
<td>Ref-Shaly Sand</td>
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<tr>
<td>Noise3:</td>
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<tr>
<td>Ref-Sand</td>
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<td>Ref-Shaly Sand</td>
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CONCLUSIONS

In this paper, we introduce a MO optimization approach using stochastic search techniques to the subsurface geosmodel updating problem. We use it to improve the geomodel estimation by simultaneously integration of multiple datasets acquired by several different geological and/or geophysical techniques for the same area. We validate the proposed MO inversion technique on a 3D reservoir litho-facies modeling problem. In fact, it is used to obtain a set of reservoir litho-
facies models reproducing the base P- and S-wave impedances derived from the pre-production seismic data. Qualitative and quantitative analysis of the results shows an acceptable match between the obtained models (the best compromise model solutions respect to the defined objectives) and the true reference model. We also show that by using the prior information in the generation of the initial population, the proposed MO inversion algorithm is computationally more efficient and yields higher quality results. The sensitivity of the model solutions to the presence of the different kinds of the noise in the seismic data demonstrated that the presented approach could result in the acceptable solutions even for noisy data.

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