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Multi-objective optimization for reservoir modelling and seismic data matching: proof of concept and field application

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SUMMARY

We present a new method to generate reservoir models by combining geostatistical simulation and optimization of multiple objective functions; including seismic data matching (i.e. a reservoir model seismic matching loop). Our method is used to estimate static reservoir models by simultaneously integrating several datasets including well logs, geologic information and various seismic attributes. The key advantage of our proposed method is that we can define multiple objective functions for a variety of data types and constraints, and simultaneously minimize the data misfits. Using our optimization method, the resulting models converge towards Pareto fronts, which represent the sets of best compromise model solutions for the defined objectives. We test our new approach on a 3D object-oriented reservoir model, where variogram-based simulation techniques typically fail to produce realistic models. Our results indicate that improved reservoir facies and porosity models and flow-unit connectivity can be obtained with this new multi-objective optimization approach.

Key words: Static reservoir models, multi-objective optimization, seismic inversion, rock physics modelling.

INTRODUCTION

Construction of reservoir models that are both geologically and geophysically realistic is of great importance for example when we want to use 4D seismic data for reservoir monitoring and characterization, and production forecasting with flow simulators. Initial reservoir models are typically built using the static data including well logs, core measurements, and baseline seismic surveys. These models are then updated in a history matching process to honour dynamic reservoir data over production time. (e.g. historical production data and time-lapse seismic data). When we include 4D seismic data in the reservoir history matching process, it is essential that synthetic seismic data modeled from the initial static reservoir model closely matches the pre-production seismic data (e.g. Lumley and Behrens, 1998; Dupin et al., 2011). Without this initial match, it would be unreasonable to match any time-lapse seismic data with reservoir simulation models. From a mathematical point of view, history matching is essentially a highly underdetermined and nonlinear inverse problem to infer reservoir properties from the historical data. According to the definition of nonlinearity (Eq. 1), a small perturbation in the initial model may cause a considerable difference in the output. Thus, in the 4D seismic history matching, it is vital process to ensure that the static reservoir model honours both initial geological and geophysical data, since it acts as a starting point for the subsequent history matching process. In other words, if the reservoir model does not honour the seismic data, how one could expect the history matched models to estimate the future performance of the reservoir accurately. On the other hand, if one could obtain a model which is tightly conditioned to seismic data, it is most probable that at least one of the several possible scenarios for static and dynamic modeling has been achieved.

$$F(m_0 + \Delta m) \neq F(m_0) + F(\Delta m), \qquad \text{(Eq.1)}$$

The methodology discussed in this paper involves generating reservoir models by optimization of multiple objective functions; including seismic data matching. Our ultimate goal is to generate geologically and geophysically consistent reservoir models to optimally initialize and hence accelerate the history matching process. In the proposed approach, we try to achieve the best compromise models for multiple goals in terms of geological knowledge, geophysical data and connectivity information through a single optimization run. We present a new approach based upon a multi-objective optimization algorithm (e.g. Singh et al., 2008) for this purpose.

A multi-objective optimization problem can be defined as finding a vector of decision variables $\vec{x}^* = [x_1, x_2, \dots, x_n]^T$ which optimize a vector of objective functions $\vec{f}(\vec{x}) = [f_1(x), f_2(x), \dots, f_k(x)]^T$ subject to p equality constraints of $h_i(x) = 0,\ i = 1,2,\dots,p,$ 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 restrictions imposed by the constraints define a feasible region within the search space ($\mathcal{F} \subseteq \boldsymbol{\mathcal{S}}$), for which any $x \in \mathcal{F}$ yields a feasible solution. The vector $\vec{x}^*$gives an optimal solution which is often non-unique (Singh et al., 2008). Inversion problems with two or more objective functions suffer from difficulties in choosing the proper weights for each term in the weighted summation of the objective functions; and hence the optimal solution is a function of the chosen weights. Turning these inversion problems into population-based techniques and taking advantage of the dominance concept is beneficial for handling such multi-objective optimization problems (An 2004).

MULTI-OBJECTIVE RESERVOIR MODEL-SEISMIC MATCHING LOOP

Our proposed approach consists of two steps: First, the relevant problem domain knowledge and prior information (geology, geophysics, rock physics, petrophysics and engineering data) are integrated to generate an ensemble of starting models through geostatistical simulation techniques. Second, a population-based multi-objective optimization is designed and implemented to perform the reservoir model-seismic matching loop process.

PROOF OF CONCEPT ON A TEST MODEL

We present a test of our approach using a 3D synthetic object-oriented reservoir model. We create a reference (true) reservoir lithology model, consisting of 38.5% channel sand and 61.5% shaly sand facies via object-based modeling in such a way that the channel sands create three potential flow units (Figure 1). We construct six pseudo-well trajectories at pre-defined positions within the reservoir 3D framework. We calculate the P-wave impedance volume for the reference litho-facies model, using a petroelastic model, designed based on theoretical and experimental rock physics relationships.

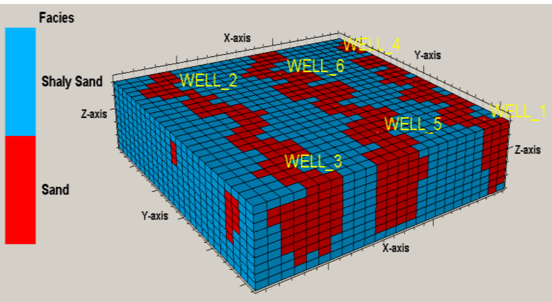

Figure 1: Reference litho-facies model.

For an efficient reservoir model seismic matching loop, the choice of objective functions is vital. In this study, we define three objective functions for litho-facies modeling and two objective functions for porosity modeling. For both litho-facies and porosity modeling, the first objective function accounts for the mismatch between the inverted and simulated seismic impedance data in a least-squares sense. The second objective function for litho-facies modeling measures the mismatch between litho-logs and the extracted facies indicators from the simulated models at well locations, and for porosity modeling it measures the mismatch between the porosity logs and the modeled porosities at well locations. The third, as an image-based objective function, accounts for the mismatch between the connectivity information derived from geologic-based simplified images of the reference and simulated seismic impedance datasets. This objective function is only defined for litho-facies modeling.

In defining the objective function-3 for litho-facies modeling, we rely on the notion that amongst a huge volume of seismic data, the most important information is contained in just a few regions and the remainder is either subject to noise and uncertainties, or is related to regions which are not critical to the reservoir static and dynamic modeling process (Derfoul, et al, 2012). For this reason, we design a workflow to define an adaptive objective function which improves the seismic match between the observed and simulated data, captures the main features observed in the seismic data, and recovers static connectivity based on observed seismic and well data.

- **Lithofacies modeling**

Once we have defined the three objective functions and selected the evolutionary stochastic optimization parameters such as population size, initial population members, cross-over and mutation fractions, we perform the petro-elastic multi-objective optimization. Figure 2 shows how solutions move towards the Pareto optimal region in the objective function space during generations. Since in the population-based MOPs, the number of objective functions is considerably less than the number of model parameters, plotting solutions in the objective space rather than model space, is a useful quality check of the model solutions. This feature of MOP is an efficient tool in our proposed reservoir model to seismic matching loop by allowing for the evaluation of accuracy, non-uniqueness and uncertainty of the results.

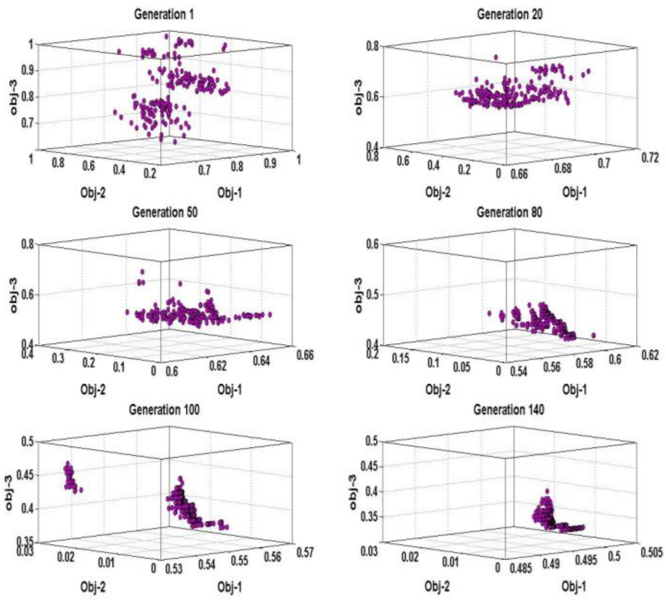

Figure 2: Solutions in the objective function space, for litho-facies modeling.

To highlight the performance of this three-objective optimization in the reservoir model seismic matching loop, the applications of single-objective, bi-objective and weighted-summation of the objective functions are also tested. Figure 3 summarizes the results in terms of the average misfit error of the obtained model solutions with the base reservoir litho-facies model. We can see that the average misfit error is 33.5% when comparing the initial reservoir models (generated by the constrained geostatistical simulation) with the reference model. When applying single-objective optimization using obj-1, obj-2 and obj-3 separately, the average misfit error of 33.5% reduces to 17.6%, 24.8% and 24.5%, respectively. The applications of the weighted summation of Obj-1 and Obj-2 with different weights show that there is no considerable reduction in the mismatch. In addition, our analysis shows that applying bi-objective optimization (Obj-1 and Obj-2) slightly decreases the average misfit error of the resulting model solutions. Finally, the figure shows that application of three-objective optimization approach considerably reduces the average misfit error of the resulting model solutions, from 33.5% in the initial reservoir models to 9.7% in the obtained models. This means that there is 23.8% improvement in the updated models.

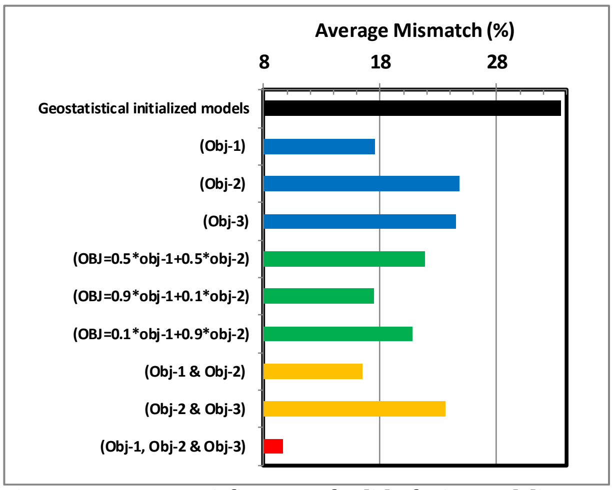

Figure 3: Average misfit errors for lithofacies modeling.

- **Porosity modeling**

For porosity modeling we perform the bi-objective optimization, while the first objective function is the seismic term and second objective function is well log term. Figure 4 shows the evolution of the objective functions for this bi-objective optimization problem for different generations (iterations). The final set of model solutions falls in the Pareto region and shows a considerable reduction in the objective function misfits.

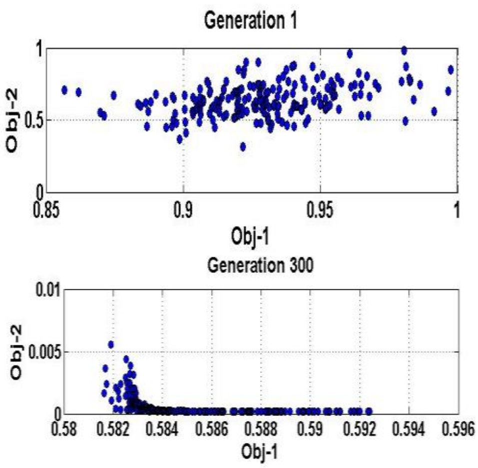

Figure 4: Solutions in the objective function space, for porosity modelling.

A performance metric is designed to measure the extent of the convergence to the reference data (optimal Pareto solutions). In this metric, minimum Euclidean distance between each of the estimated solution and true solution is computed. The average value of these distances is used as a measure of convergence performance. When the metric takes the value of zero, means that all the obtained solutions lies on Pareto optimal solution. The smaller the mean value of performance metric is an indicator of better convergence toward true solution. The comparison of the mean values of this metric for the initial porosity models and the final sets of porosity models show 42% improvements in the porosity estimation after 300 generation. In figure 5a, the porosity histograms of reference model and average realization of the initial models and in figure 5b, the porosity histograms of the reference model and average realization of the final sets of models after bi-objective optimization are shown. It is evident that the porosities obtained by our proposed bi-objective optimization approach have much better match with the actual reference porosity model.

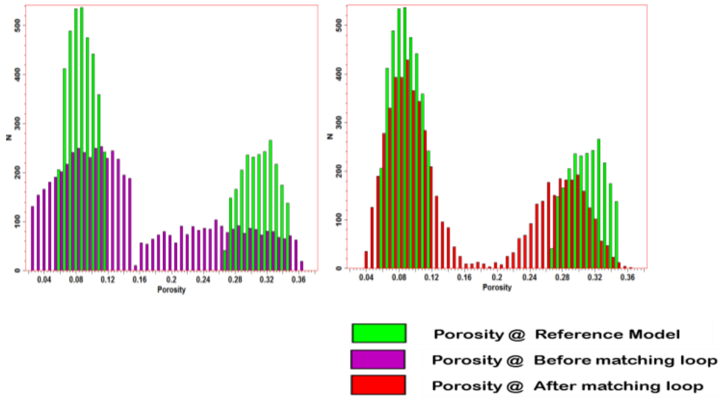

Figure 5: (a) porosity histograms of reference model and mean realization of the initial models and, (b) porosity histograms of the reference model and mean realization of the final sets of models after bi-objective

FIELD DATA EXAMPLE

The Stybarrow field is located in the Exmouth sub-basin of the Carnarvon Basin, offshore Western Australia. The approximate water depth over the field location is 800 m. In the Stybarrow structure, oil is trapped in the high quality sandstones of the Macedon Formation. The intersection of the E-W and NNE/NE trending normal faults develop a triangular oil trap. Top, base and bounding-fault seals are provided by siltstones and claystones of either overlying or underlying geologic formations (Ementon et al. 2004, Hill et al. 2008).

A complete set of well logs at four wells, and a set of three migration angle stack seismic volumes, were available for this study. Rock physics analysis using elastic well logs reveals that P-impedance, Vp/Vs and density are the best seismic elastic attributes to discriminate different facies classes in the studied reservoir. Therefore, we performed simultaneous elastic parameter inversion using near, mid and far angle stack volumes for Stybarrow field. The prestack inversion process generates volumes of seismic elastic attributes. In Figure 6 cross-sections of the inverted density and Vp/Vs around well no.1 are shown.

In this field example of multi-objective reservoir model-seismic matching loop, we concentrate on creating facies-based reservoir models. A number of different facies have been identified in the Stybarrow reservoir. However, high net-to-gross values along with small variations in petrophysical properties within the facies led us to simplify the reservoir into a Net and Non-Net facies system.

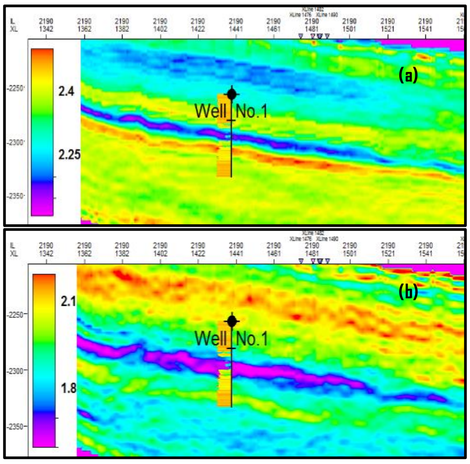

Figure 6: (a) Inverted density, and (b) inverted Vp/Vs.

The first and second objective functions measure the mismatch between the inverted and synthetic Vp/Vs ratio and P-impedance seismic data volumes, respectively, in a least-squares sense. This ensures the resulting models are constrained to match the seismic data. The third (image-based) objective function measures the mismatch between information derived from geologic-based image interpretation of the seismic data. This ensures that the resulting models are constrained by interpreted geologic features and patterns. Figure 7a shows the average of the initial reservoir model realizations, and Figure 7c shows the average of the final set of optimal models after applying the multi-objective optimization. To understand the improvements in the final models, the corresponding connected volumes of Net facies for each of the average initial and final models are shown in Figures 7b and 7d respectively. Evidence from dynamic production data collected at Stybarrow such as interference tests, injection tracers, reservoir bottom-hole pressure and 4D seismic (Hurren, et al. 2012) indicates that the connected flow units are better represented in the reservoir models after the multi-objective optimization, whereas the initial geostatistical reservoir models do not correctly represent the known reservoir connectivity.

CONCLUSIONS

We have introduced a new approach for the reservoir model seismic matching loop by combining geostatistical simulation and multi-objective optimization. It is used to improve static reservoir model estimation by simultaneously integrating multiple datasets including well logs and seismic data. We designed a test case with a multi-objective optimization problem in order to estimate reservoir litho-facies and porosity models. Qualitative and quantitative analysis of the results shows an improved match between the estimated model solutions (the best compromise model solutions respect to the defined objectives which exist on the Pareto front) and the true reference model. We also use it to improve reservoir models for an Australian field by simultaneous integration of seismic data, geologic information and well logs acquired at the field.

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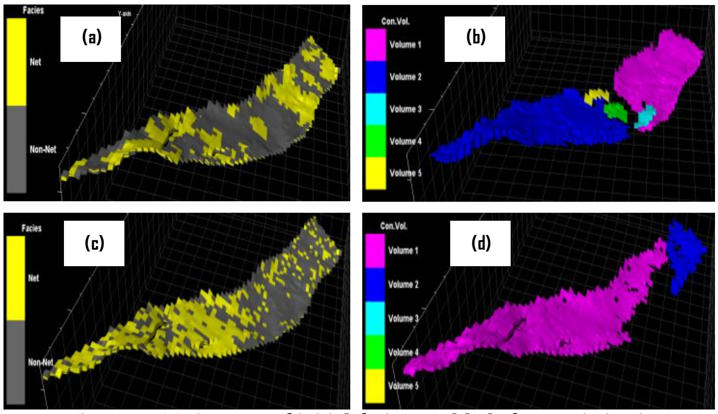

Figure 7: (a) Average of initial facies models before optimization, (b) connected volumes of Net Facies in average of initial models, (c) average of final facies models after optimization, and (d) connected volumes in average of final facies models after optimization (which match dynamic production data estimates of connectivity).

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