Assessing the Value of Sensor Information in 4-D Seismic History Matching

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Summary

The main objective of the present work is to numerically determine how sensor information may aid in reducing the ill-posedness associated with permeability estimation via 4-D seismic history matching. These sensors are assumed to provide timely information of pressures, concentrations and fluid velocities at given locations in a reliable fashion. This information is incorporated into an objective function that additionally includes production and seismic components that are mismatched between observed and predicted data. In order to efficiently perform large-scale permeability estimation, a coupled multilevel, stochastic and learning search methodology is proposed. At a given resolution level, the parameter space is globally explored and sampled by the simultaneous perturbation stochastic approximation (SPSA) algorithm. The estimation and sampling performed by SPSA is further enhanced by a neural learning engine that estimates sensitivities in the vicinity of the most promising optimal solutions. Preliminary results shed light on future research avenues for optimizing the frequency and localization of 4-D seismic surveys when sensor data is available.

Introduction

The continuous growth of computing power, sensor and communication technology is bridging gaps in understanding several fields in the geosciences. Specialized sensors are capable of measuring at a high local resolution, fluid and rock properties (see e.g., Lumley, 2001, Versteeg et al., 2004, Hornby et al., 2005, and references therein). These advances, in conjunction with 4-D time-lapse seismic studies, are revealing enormous potentials to reduce the uncertainty in both reservoir characterization and production scenarios. Meanwhile, new stochastic optimization and statistical learning methods are arising as promising tools to find nontrivial correlations between data measurements and responses and to develop optimal reservoir exploitation plans (van der Baan and Jutten, 2000, Nikravesh, 2004, Klie et al., 2004, Spall, 2004, Keane and Nair, 2005).

The main objective of the present work is to numerically assess the value of sensor information in 4-D seismic history matching. To that end, we will assume that reliable sensor information may be available at any time and at any reservoir location. Despite the fact that this analysis may explore far beyond customary industrial practice, our main motivation is to evaluate, from a numerical standpoint, the potentials that sensor technology may have in reservoir characterization. This work involves a comparative analysis of different sensor-based objective functions and the introduction of a new methodology to eventually tackle large-scale parameter estimation problems. The set of objective functions evaluates the impact that the addition of sensors for pressure, concentration and fluid flow velocity has in the quality of the permeability estimation. This allows us to relate detailed changes in fluid flow and seismic traveltimes to permeability field distribution.

The proposed 4-D seismic history matching methodology consists of the use of a multilevel approach to gradually perform parameter estimation from low to high resolution levels. The combination of global stochastic searches with local estimations via artificial neural networks (ANNs) provides means to perform sensitivity analysis and further refinements to the parameter estimation process. The whole methodology comprises the integration of multiphase flow simulation, petrophysics (via Biot-Gassmann's theory) and traveltime seismic modeling in the evaluation of the objective function. An important component of the whole methodology is illustrated on a coarse but realistic 2-D data-set. Preliminary results reveal that sensor-based reservoir characterization may provide important guidelines as to how time-lapse 4-D seismic studies should be effectively performed.

A Sensor-based Seismic History Matching Methodology

The proposed methodology consists of the use of a multilevel approach to gradually perform parameter estimation from low- to high-resolution levels. We restrict our attention to permeability although the proposed framework could also be employed for other reservoir parameters of interest, such as porosity, PVT data, stress and fracture distribution. An initial upscaling process is carried out via wavelet transformations, and the downscaling propagates the best permeability estimation from coarser to finer simulation grids. As the resolution is increased, the amount of computation is systematically decreased in order to achieve further efficiency. This is illustrated in Figure 1.

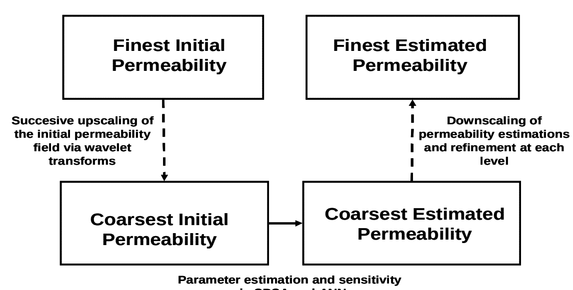

Figure 1. Multilevel approach for permeability estimation.

Starting from the coarsest grid, the parameter estimation is first carried out with the simultaneous perturbation stochastic approximation (SPSA) algorithm (Spall, 2003) with different initial guesses. This not only augmentd the chances for finding a global optimal solution, it also allows for a rich sampling of the parameter space. Moreover, the search performed by the SPSA algorithm guides the sampling toward promising regions containing a global solution ("hot spots"). We provide more details on the SPSA algorithm below. Due to the size of the coarse grid, thousands of computations are affordable in a few hours. Based on the mapping between parameters and the objective function, we generate an artificial neural network (ANN) that allows us to perform sensitivity analysis and further refine the solution of the optimization. Therefore, points evaluated by the ANN are validated against the simulator. If these evaluations lead to a better optimizer, then the final estimation is used as an initial guess for the next finer resolution permeability grid. In this way, the ANN acts as a surrogate model or metamodel for the simulation model. Figure 2 illustrates this process for a given permeability resolution level.

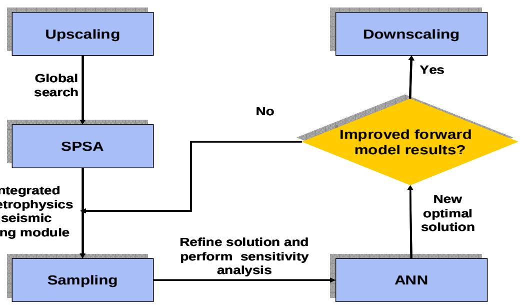

Figure 2. Permeability estimation at each resolution level.

The simulation model consists of the integrated functionality of independent multiphase flow, petrophysics and seismic models. The flow component is provided by the Integrated Parallel Accurate Reservoir Simulation (IPARS) framework (Wheeler, 1998). The petrophysics model follows the Biot-Gassman theory, which describes seismic velocity changes resulting from changes in pore-fluid saturations and pressures. Given the resulting seismic velocities, it is possible to perform wave propagation modeling through the porous media. In the first stage of the present effort, we are momentarily disregarding amplitude effects and, instead, reporting on traveltime measurements generated by a raytracer algorithm. Therefore, the simulation model allows us to evaluate a collection of objective functions of the form:

$$\Phi(\mathbf{p},\mathbf{c},\mathbf{u},\mathbf{q},\tau) =$$
$$\sum_{i=1}^{T}\left[\left\|\mathbf{w}_{p,i}\left(\mathbf{p}_i^d-\mathbf{p}_i\right)\right\|_2+\left\|\mathbf{w}_{c,i}\left(\mathbf{c}_i^d-\mathbf{c}_i\right)\right\|+\left\|\mathbf{w}_{u,i}\left(\mathbf{u}_i^d-\mathbf{u}_i\right)\right\|_2\right]+$$
$$\sum_{i=1}^{T}\left[+\left\|\mathbf{w}_{q,i}\left(\mathbf{q}_i^d-\mathbf{q}_i\right)\right\|_2+\left\|\mathbf{w}_{\tau,i}\left(\tau_i^d-\tau_i\right)\right\|_2\right],$$

where ***p***, ***c*** and ***u*** denote pressure, concentration and velocity vectors at discrete times, respectively. Here, ***q*** represents data at production wells, i.e. bottom hole pressure, gas/oil ratio and cumulative production. The variable τ stands for the traveltime vector. Superscript *d* indicates measured data. The weight operators, $\mathbf{w}_x$, include scaling factors and allow for the flexible selection of sensor, production and seismic measurements. Note that the above formulation may include measurements at selected locations and at discrete times throughout the simulation interval *[0,T]*.

Simultaneous Perturbation Stochastic Approximation

The simultaneous perturbation stochastic approximation (SPSA) algorithm has received considerable attention for global optimization problems where it is difficult or impossible to compute first order information associated with the problem. SPSA performs random simultaneous perturbations of all model parameters to generate a descent direction at each iteration. Despite the random character of the procedure, the expected value of the computed direction is the deterministically steepest descent direction. One of the most attractive features of the SPSA algorithm is its simplicity, flexibility and low computational cost. This algorithm only requires one or, at most, two function evaluations per iteration independently of the parameter space size in order to generate a stochastic descent direction. This means that the method does not require further modifications to the simulation model (i.e., a black-box approach). This is very convenient due to the size of the parameter space and the complexity of the current simulation model. Promising SPSA results have already been reported in several engineering and scientific scenarios (Spall, 2003).

The Neural Learning Engine

The ANN implementation of the present work considers a multilayer perceptron architecture under the supervised learning framework. Supervised learning implies the existence of a "teacher" or "adviser" entity, which is responsible for quantifying the network performance. In many practical applications, this reduces to the availability of a set of input data for which the expected output data is known. This input data, along with its corresponding output data, constitutes the training data set for the multilayer perceptron. Such a training set should be split into three sets: training, test and cross-validation; which should be used in both experimentation phases: the first one regarding the ANN parameter calibration, and the second one regarding the final training of the ANN for the application under consideration. The training of the multilayer perceptron considered here is implemented by using the classical back-propagation algorithm, which is based on the error-correcting learning rule derived from the optimal filtering theory. In the application developed here, the ANN engine is used with a double objective in mind. The first one has to do with capturing the intrinsic complexities of the mismatch objective function with respect to variations of the permeability field values in a given neighborhood of suboptimal reservoir parameters. This will enable performance of fast sensitivity analyses of each individual model parameter with respect to the overall system response, which will provide useful information about the specific locations where multiple scale refinements are required. The second objective regards the ability to provide an efficient and smooth estimator of the mismatch objective function in a given neighborhood of suboptimal reservoir parameters, which will lead to more robust and faster parameter estimation.

Numerical Examples

Computational experiments were performed on a coarse grid representation of model 1 of the SPE 10th Comparative Solution Project (Christie and Blunt, 2001). The main objective of this preliminary set of experiments was to evaluate the implications that sensor technology may have in complementing 4-D seismic history matching in a rather exhaustive fashion. The original permeability field is shown in Figure 3 and consists of a cross-sectional reservoir model with 1x100x20=2000 gridblocks. The size of each grid block is 25x25x2.5 ft^3. The reference coarse permeability field, consisting of 1x10x2=20 gridblocks, is obtained by successive upscaling using the Haar wavelet (Daubechies, 1992). The original reservoir model was slightly modified to allow for oil and gas compressibility and capillary forces due to the interaction of these two phases. A fixed production strategy was adopted with one gas injecting well located at the leftmost side of the model and a production well at the opposite side. Sensor measurements were assumed to be a) inactive, b) active along the wellbore, c) active midway between the two wells and along the wellbore and, d) active at every grid cell. Sensors were able to provide timely (i.e., at each simulation step) measurements of pressures, concentrations and flow velocities. A cross-well raytracing modeling was performed

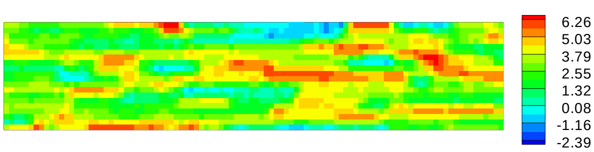

Figure 3. Original high resolution permeability field.

every 90 days for this well configuration. An initial guess for the parameter estimation was generated by means of the singular value decomposition (SVD) that considered only the first three resolution components (out of 2000) from the fine grid reference data. In this way, some of the features of the original permeability field were somewhat captured. Each iteration of the SPSA algorithm involved two function evaluations, where each of them implied the execution of a coupled flow, petrophysics and seismic simulation model for T= 1000 days (~3 years) on a different permeability field configuration. The SPSA algorithm was able to converge to the desired tolerance (1.e-5) in less than 1000 iterations.

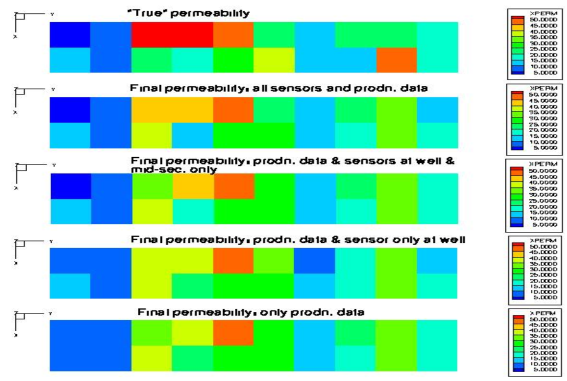

Figure 4. Permeability estimation as sensor observations are added into the inversion process.

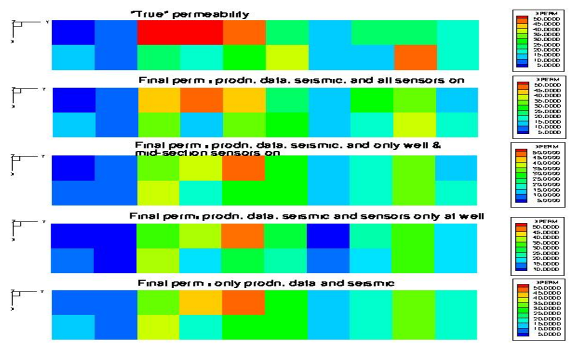

Figure 5. Permeability estimation as sensor observations are added with seismic observations into the inversion process.

In all cases considered, well production data (oil production rates, GOR and cumulative oil production) were matched reasonably well (not shown here). Only a slight mismatch error was noticeable when the inversion was performed solely on production measurements. Figure 4 shows the permeability estimation using different degrees of sensor information without the use of seismic information. Clearly, the more sensors are added the higher the quality of the permeability estimation. However, in spite of considering the hypothetical situation of having sensors everywhere, the reference permeability is never recovered. In general, the estimation presents more difficulties in adjacent cells showing higher contrasts.

Figure 5 presents the permeability estimation with the inclusion of seismic measurements. The estimations display a similar global trend as in Figure 4. Nevertheless, the inclusion of seismic measurements introduces some important estimation enhancements as panels from both figures are compared one by one. We can see that the permeability estimation based on both production and seismic data is comparable to using both production and sensor data from the wellbore. As more sensors are added, we can observe how the quality of the estimation improves in the locality of the sensor. This shows that sensor data have a local resolution effect in contrast to the global effect that seismic and production data have in the estimation process. A comparison was also made for pressures, concentrations and flow velocities at different gridblocks, showing a similar trend. We note that concentrations were harder to obtain than pressures and flow velocities harder to obtain than concentrations in the estimation process.

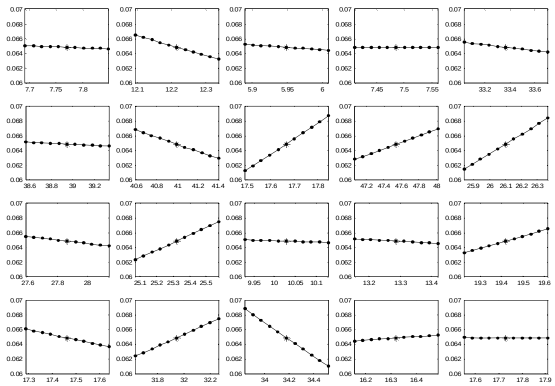

Figure 6. Sensitivity results using the ANN.

Figure 6 depicts the sensitivity results obtained from the ANN in the case that the estimation relies only on production and seismic data (no sensor information). Each panel (numbered in a row-wise fashion) corresponds to a computational gridcell. We can see that cells 2, 7, 8 and 9 in each horizontal layer are the most sensitive ones. This implies that further refinement of the estimated solution in those cells can be obtained by means of a local optimization procedure (e.g., Newton or quasi-Newton method). Moreover, the degree of sensitivity may suggest that additional information in those cells would be of value for further constraining the search space and, thereby enhancing the quality of the estimation. In fact, the more sensors that are added into the estimation the less steep the sensitivity curves are. This illustrates how additional information tends to smooth out the search space.

Conclusions and Further Remarks

Despite the fact that we have employed a coarse model for this preliminary phase of the project, we can draw some important conclusions:

1. The history matching is improved as more information is added to the objective function, clearly indicating that sensor information can help in reducing the uncertainty associated with reservoir characterization.
2. It is possible to match the production results using only production data in the objective function. However, this does not necessarily yield reliable permeability estimations due to the inherent ill-posedness of the inversion process.
3. Time-lapse 4-D seismic measurements provide global insight into the history matching process that neither production data nor localized sensor information on fluid properties is able to reproduce.
4. The combination of SPSA and ANN is very attractive for parameter estimation purposes, especially when the problem complexity makes derivative computation unfeasible. Moreover, this type of hybrid approach may be convenient when models and data are subject to dynamic changes as the understanding of the reservoir increases.

Ongoing efforts are currently focused on a deeper analysis of the value that sensor information has in 4-D seismic history matching. To that end, the research team is currently exploiting both multilevel and surrogate model approaches for enhancing the estimation when thousands of parameters are involved.

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