A LEARNING COMPUTATIONAL ENGINE FOR HISTORY MATCHING

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Abstract

The main objective of the present work is to propose and evaluate a learning computational engine for history matching, which is based on a hybrid multilevel search methodology. According to this methodology, the parameter space is globally explored and sampled by the simultaneous perturbation stochastic approximation (SPSA) algorithm at a given resolution level. This estimation is followed by further analysis by using a neural learning engine for evaluating the sensitiveness of the objective function with respect to variations of each individual model parameter in the vicinity of the promising optimal solution explored by the SPSA algorithm.

The proposed methodology is used to numerically determine how additional sources of information may aid in reducing the ill-posedness associated with permeability estimation via conventional history matching procedures. The additional sources of information considered in this work are related to pressures, concentrations and fluid velocities at given locations in a reliable fashion, which in practical scenarios might be estimated from high resolution seismic surveys, or directly obtained as *in situ* measurements provided by sensors. This additional information is incorporated, along with production data, into a multi-objective function that is mismatched between the observed and the predicted data. The preliminary results presented in this work shed light on future research avenues for optimizing the use of additional sources of information such as seismic or sensor data in history matching procedures.

1. Introduction

Learning technologies have helped oil industry exploration and production in finding nontrivial correlations between data measurements and responses (see e.g., van der Baan and Jutten, 2000; Nikravesh, 2004). Nevertheless, these efforts have been primarily incorporated in an isolated fashion within the oil industry practice. On the other hand, the continuous growth of computing power, sensor and communication technology is bridging the gap between several fields in geosciences for the common goal of reducing uncertainty for achieving better subsurface understanding and producing more reliable decisions (see e.g., Lumley, 2001; Versteeg et al., 2004; Hornby et al., 2005, and references therein). Time-lapse seismic for history matching is also a relevant example of how this technology is making possible to further constrain the parameter search space and produce better reservoir characterizations.

The present work is concerned about jointly learning from production observations and other additional sources of information, and being able to relate detailed changes in the observed data into valuable permeability distributions. Furthermore, the present research aims at determining the value these additional sources of information have in the overall history matching process. More specifically, we investigate how information contained in state variables such as pressure, concentration and flow velocities may aid at improving the quality of the overall parameter estimation. To that end, we proposed a hybrid methodology based on the coupling of a neural network estimation engine (ANN) with the simultaneous perturbation stochastic approximation (SPSA) algorithm to be able to perform an efficient minimization of the output error criteria and guidance of the self-learning process. The optimization framework includes a multi-scale approach to gradually perform the estimation from low to high resolution levels (Rodriguez et al., 2006).

The proposed ANN implementation considers a multilayer perceptron architecture under the supervised learning framework that is trained by means of the classical back-propagation algorithm. Regarding the simulation model, the methodology comprises the full integration of multiphase flow simulation into the mismatch history matching function. The concept of using ANN with stochastic optimization (via SPSA) for intelligence amplification in history matching is illustrated on a realistic 2D data-set. Although the proposed framework could also be employed for other reservoir parameters of interest, such as porosity, PVT data, stress and fracture distribution; for simplicity reasons we restrict our attention to permeability.

The structure of the present paper is as follows. First, we provide a brief description of the optimization framework, emphasizing the formulation of the multi-objective function, parameterization and the integrated flow simulation model. Section 3 presents a brief description of the SPSA algorithm. Section 4 describes the ANN approach and its role for performing sensitivity analysis of the multi-objective mismatch function. Section 5 shows the numerical experiments and section 6 presents the conclusions and further research avenues of this work.

2. Optimization Framework

2.1 Fundamentals

The current methodology is based on a multi-scale treatment of the parameter space (Rodriguez et al., 2006). This is achieved by decomposing the log of the original permeability (or porosity) field in a summation of different *eigenimages* that are obtained by the singular value decomposition (SVD). Each of these *eigenimages* represents a resolution level of the original parameter space whose relevance (or energy content) is controlled by the associated singular value. Thus, the problem is parameterized in terms of singular values and the determination of each one of them provides a level of resolution in the parameter space.

The second step is to generate further resolution levels with the successive application of wavelet transforms on each *eigenimage*. Due to the linear character of wavelet transforms, the value of the parameters to estimate can be preserved at different scales. This allows for obtaining good estimations for higher parameter values (those associated with low-resolution levels) in an inexpensive computationally manner. In this way, the number of estimated variables increases as finer resolution levels are progressively included.

At each resolution level, we use the simultaneous perturbation stochastic approximation (SPSA) method to perform a broad search for the optimal solution. The SPSA algorithm produces a systematic sampling on the parameter space which is richer in a neighborhood of the optimal solution. This sampling can be used to construct a metamodel (i.e., surrogate model) based on the response surface. In our particular case, the sampled points are training points for an artificial neural network (ANN). Despite that there are other methods for constructing metamodels (Keane and Nair, 2005), the ANN can capture complex and nonlinear multivariate relations in the presence of noise. Figure 1 illustrates how the SPSA and ANN are coordinated to enhance the parameter estimation process.

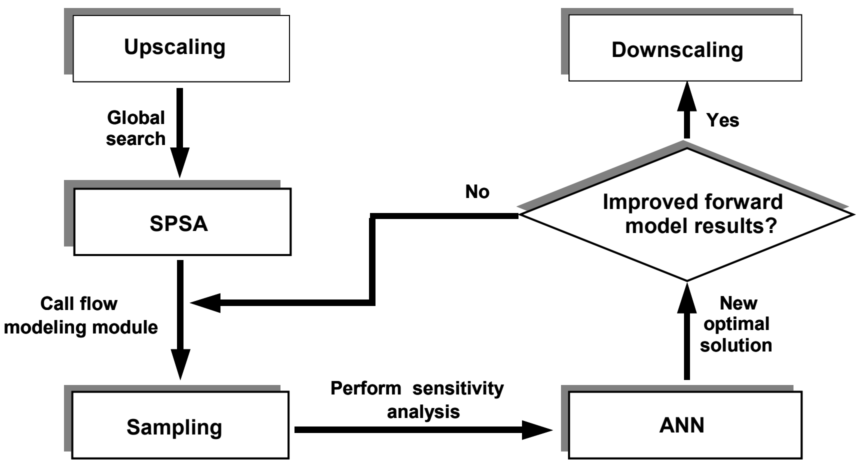

Figure 1. Parameter estimation at each resolution level.

2.2 Integrated Multiphase Flow

The forward model comprises a multi-scale flow reservoir simulator. The flow component is given by the IPARS (Integrated Parallel Accurate Reservoir Simulator) framework. An attractive feature of IPARS is that it allows for the coupling of different models in different subdomains and supports message passing for parallel computations on structured multi-block meshes in two and three space dimensions (M.F. Wheeler and M. Peszynska, 2002).

2.3 Objective Function

The complete objective function accommodates several components that account for mismatch values of simulated production, and the three state variables of pressure, concentration and flow velocities, with respect to field measurements:

$$\mathrm{F}\,(p, c, u, q) = \sum_{i=1}^{t} \Big[\, \|W_{pi}\,(p_i^d - p_i(\theta))\|_2 + \|W_{ci}\,(c_i^d - c_i(\theta))\|_2 + \|W_{ui}\,(u_i^d - u_i(\theta))\|_2 + \|W_{qi}\,(q_i^d - q_i(\theta))\|_2 + \|W_{\theta i}\,(\theta - \theta_{prior})\|_2 \,\Big] \tag{1}$$

where p, c and u denote the pressure, concentration and flow vectors at discrete times, respectively. Here, q represents data at production wells, i.e. bottom hole pressure, gas/oil ratio and cumulative production. Superscript d indicates measured data. The last term represents the constraint given by the model parameters θ based on some *a priori* information. Recall that these model parameters are singular values and result from the parameterization of the original reservoir parameters. The weight operators, W_*, include scaling factors and allow for the flexible selection of each different measurements at specific experimental setting. These operators integrate the definition of covariance operators. The above formulation includes measurements at selected locations and at discrete times throughout the simulation interval *[0,t]*.

3. Global Optimization via SPSA

The SPSA algorithm has received considerable attention for global optimization problems where it is unfeasible to compute function gradients. 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. The SPSA for equation (1) is defined by the following recursion:

$$\theta_{k+1} = \theta_k - a_k g_k(\theta_k), \tag{2}$$

where a_k is a positive scalar that monotonically decreases with respect to k, and $g_k(\theta_k)$ is a stochastic approximation to the gradient given by a simultaneous perturbation of all elements of θ_k, that is,

$$g_k(\theta_k) = \frac{1}{2}\left[\Phi(\theta_k + c_k\Delta_k) - \Phi(\theta_k - c_k\Delta_k)\right]\Delta_k^{-1}, \tag{3}$$

where c_k is also a positive scalar that monotonically decreases with respect to k, Δ_k is a vector consisting of *{–1,1}* values randomly generated with a Bernoulli distribution and Δ_k^{-1} stands for the component-wise reciprocal of each of the entries of Δ_k. The parameters a_k and c_k form a monotonically decreasing sequences with respect to k that are chosen to ensure asymptotic convergence of the algorithm; for more details and pointers on SPSA see (Spall, 2003).

One of the most attractive features of the SPSA algorithm is its simplicity, flexibility and low computational cost. As can be seen from (3), the 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 for (2). 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.

4. The Learning Neural Network Engine

4.1 Fundamentals

The ANN implementation used in this work considers a multi-layer perceptron architecture under the supervised learning framework (Haykin, 1994). Supervised learning implies the existence of a "teacher" entity 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. In the case under consideration, this data is numerically generated by the SPSA while exploring a specific region of the objective function close to a promising optimal solution.

These parameter space samples, along with their corresponding objective function values, constitute the training data set for the ANN model. Such a training set should be split into three sets: training, test and cross-validation, in order to calibrate the multi-layer perceptron parameters, as well as for the final training of the ANN model. The training of the ANN is implemented by using the classical back-propagation algorithm, which is based on the error-correcting learning rule derived from the optimal filtering theory (Haykin, 1991).

In the application developed here, the ANN engine is used for constructing an efficient and smooth estimator of the mismatch objective function in the given neighborhood of optimal reservoir parameters, which will allow for capturing the intrinsic complexities of the mismatch objective function with respect to variations of the model parameter values in a more robust and faster manner.

4.2 Sensitivity analysis

According to the proposed methodology, the ANN engine allows for capturing the mismatch objective function variations with respect to model parameter values in the given neighborhood of the promising optimal solution already explored by the SPSA. This will enable the performance of a fast sensitivity analysis of each individual component of the multi-objective function defined in (1) with respect to variations of each individual model parameter. Figure 2 illustrates the overall process of SPSA space exploration and the subsequent multi-objective function sensitivity analysis.

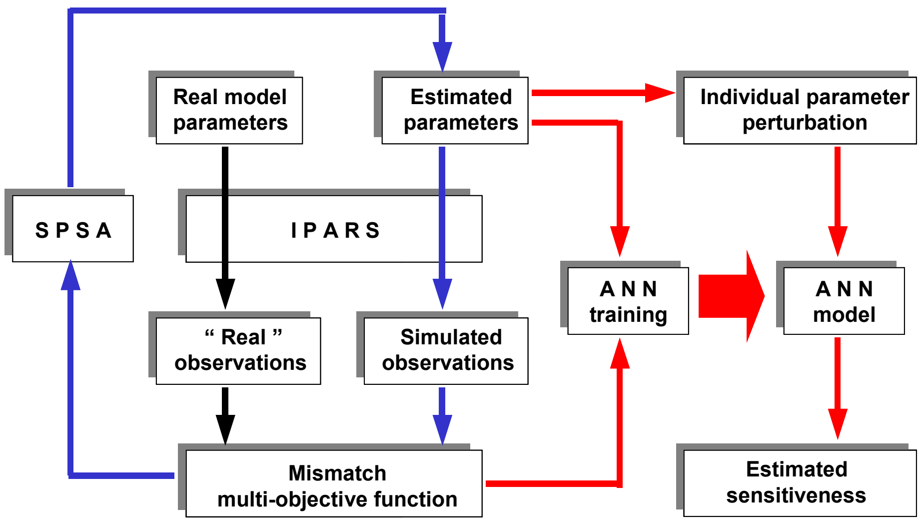

Figure 2. SPSA space exploration and multi-objective function sensitivity analysis.

The performance of this type of sensitivity analysis provides very useful information about the relative impact that each specific information component of the objective function has on the overall history matching process. In a similar way, it also provides valuable information for performing further resolution refinements to the parameter model in a more efficient and appropriate manner.

Two important considerations must be taken into account. First, special attention should be paid to the sampling process performed by SPSA in order to ensure collected samples to provide a good representation of the parameter space and then guarantee an appropriate ANN model training. Hence, several runs of SPSA within the same neighborhood might be necessary to ensure a good parameter space representation. Second, special care must be taken when performing the sensitivity analysis since the ANN representation is only valid inside the core region explored by the SPSA. According to this, the sensitivity analysis should be restricted to model parameter variations within the valid area of representation.

6. Experimental Results

Computational experiments were performed on a coarse grid representation of a cross-sectional reservoir model consisting of 20x100 grid-blocks. The size of each grid-block was 25x25x2.5 ft^3. A reference coarse permeability field, consisting of 5x25 = 125 grid-blocks, was obtained by successive upscaling using the Haar wavelet. Figure 3 shows the fine and resulting coarse permeability field. The main objective of this preliminary set of experiments was to evaluate the implications that additional information provided by state variables such as pressure, concentration and flow velocities have in complementing production data history matching.

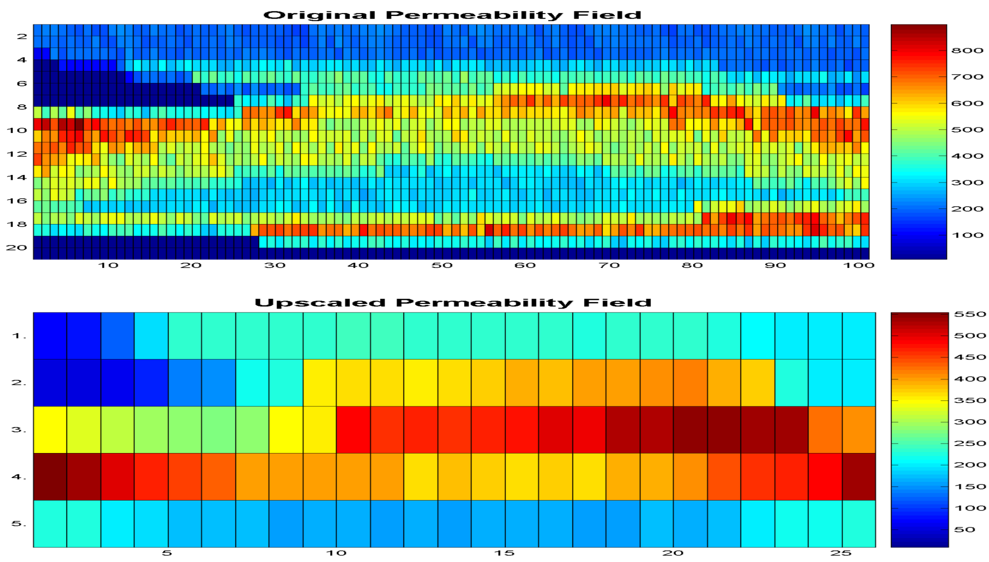

Figure 3. Original permeability field (top) and upscaled version (bottom).

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. In the experimental setting considered here, state variable measurements were assumed to be available midway between the two wells and along the wellbore. Timely (i.e., at each simulation step) measurements of pressures, concentrations and flow velocities were considered. 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 20) 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 the flow simulation model for $t = 1000$ days on a different permeability field configuration. The SPSA algorithm was able to converge to the desired tolerance (1.e-5) in 674 iterations. Once convergence was achieved, the ANN model was trained by using the sample points generated by the SPSA algorithm. An ANN architecture of two hidden layer with 8 and 4 processing units, respectively, was empirically selected. Afterwards, ANN-based models were trained for each multi-objective function component individually: production, pressure, concentration and flow velocity. An additional ANN-based model was trained for the combined contribution of the three non-production information components.

A sensitivity analysis was performed for each multi-objective function component and the combined non-production component with respect to the individual variations of each of the four resolution model parameters. Table 1 presents the resulting percentage variations for each objective function component when perturbing each of the model parameters from –0.5% to +0.5% of its final SPSA convergence value. Each percentage variation reported in table 1 actually corresponds to the mean value of 30 independent ANN model simulations, for which a confidence interval is also provided by means of the corresponding standard deviations.

Table 1: Percentage variations of objective function components with respect to model parameter variations of 1%.

Information	Component	Parameter 1	Parameter 2	Parameter 3	Parameter 4
Production	Production	56.76 ± 8.45	17.70 ± 1.69	0.54 ± 0.11	2.32 ± 0.31
Non-production	Pressure	80.47 ± 1.97	0.95 ± 0.09	0.39 ± 0.02	0.22 ± 0.02
	Concentration	37.29 ± 2.75	16.47 ± 0.92	0.67 ± 0.06	2.23 ± 0.15
	Fluxes	23.49 ± 2.01	10.95 ± 0.49	0.49 ± 0.03	1.09 ± 0.10
	Combined	45.27 ± 3.05	11.29 ± 0.61	0.34 ± 0.05	1.47 ± 0.12

Some interesting observations can be drawn from table 1. First of all, notice that all objective function components are sensitive the most to variations of the first low-resolution parameter, and much less sensitive to variations of the higher-resolution parameters. It is also very interesting the fact that all evaluated function components seem to be totally insensitive to model parameter 3. This observation has been independently confirmed by (Rodriguez et al., 2006). Thus, resolution parameter 3 does not provide any valuable information for the permeability model under consideration.

Another important observation has to do with the fact that although the production component of the multi-objective function seems to be more sensitive to model parameter variations than the combined non-production data component, it is evident from the sensitivity analysis that non-production data also should be able to provide useful information for model parameter optimization. Indeed, notice that confidence intervals are generally smaller for the non-production related components. This suggests that these information components can help reducing the overall uncertainty associated to the history matching process.

Finally, it is of special interest the behavior of the pressure component of the multi-objective function, which exhibits the largest sensitiveness with respect to the lowest resolution parameter, while being practically insensitive to all other three parameters. This seems to suggest that pressure measurements are the most fundamental component for determining basic geological structures whereas fluxes and concentrations (or saturations) play a bigger role in capturing details of the reservoir.

7. Conclusions

According to the preliminary results presented in this work, the proposed methodology promises to provide a very attractive framework for parameter estimation via history matching, especially when the problem complexity makes derivative computation unfeasible and when computational times strongly limit the search performance. As already discussed, ANN models aid at better understanding the search space in the vicinity of a promising solution by means of a sensitivity analysis. This kind of analysis provides valuable information about the relative contributions of each model parameter and multi-objective function component to the overall history matching process.

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 can be improved as more information is added to the objective function. It was shown how additional information components can actually 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. The combination of SPSA and ANN is very attractive for parameter estimation and analysis 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 and high resolution seismic data have in history matching. To that end, the research team will continue evaluating the proposed framework by incorporating both travel-time and amplitude related seismic information, as well as sensor data.

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