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Case study

Performance comparison of several response surface surrogate models and ensemble methods for water injection optimization under uncertainty

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ABSTRACT

In this paper we defined a relatively complex reservoir engineering optimization problem of maximizing the net present value of the hydrocarbon production in a water flooding process by controlling the water injection rates in multiple control periods. We assessed the performance of a number of response surface surrogate models and their ensembles which are combined by Dempster–Shafer theory and Weighted Averaged Surrogates as found in contemporary literature works. Most of these ensemble methods are based on the philosophy that multiple weak learners can be leveraged to obtain one strong learner which is better than the individual weak ones. Even though these techniques have been shown to work well for test bench functions, we found them not offering a considerable improvement compared to an individually used cubic radial basis function surrogate model. Our simulations on two and three dimensional cases, with varying number of optimization variables suggest that cubic radial basis functions-based surrogate model is reliable, outperforms Kriging surrogates and multivariate adaptive regression splines, and if it does not outperform, it is rarely outperformed by the ensemble surrogate models.

1. Introduction

The inherent uncertain nature of the geological models—due to the sparseness and scarcity of data over vast physical domains—require the designer to assume multiple geological realizations to predict flow. This adds up prohibitive computational costs to already demanding single-realization models. Moreover, the control parameters for the fluid injection and production wells in the industrial scale are often numerous and are subject to operational constraints and time-dependent uncertainties. This also makes the computational domain of the optimization problem large and consequently difficult, if not impossible, to handle for even the modern computing systems. Surrogate models are an attractive option in such circumstances. Surveys of implementation of surrogates for optimization purposes in broad engineering applications can be found in Jin (2005) and Jin (2011). The improvement of computational efficiency of surrogate-based optimization compared to the traditional optimization such as genetic algorithm has been shown in Ong et al. (2003).

The surrogate models are however approximations of the original objective functions, therefore they might introduce artificial optimal solutions which do not exist in the original objective function (Jin, 2011) and lead to premature convergence. Also the techniques have shown a strong dependence on the complex dynamics of the non-linear interactions in the model, dimension of the design space, etc. (Zubarev, 2009). Therefore a proper surrogate model management strategy is very important (Jin, 2011). The choice of a particular surrogate model is also problem-dependent and for a given problem, it is not trivial to decide which surrogate model would give the best optimization result. It has been shown that one surrogate model might give good results for a particular problem while it might perform very poorly when applied to another problem (Viana and Haftka, 2008). One solution to these shortcomings might be to improve the accuracy of the surrogates so that they are less prone to over-fitting and have more generalization capabilities for unseen solution points (Jin et al., 2002).

Another approach can be the use of multiple surrogate models (Goel et al., 2007) which have been shown to be beneficial from the optimization point of view. In this line of research, Zhou et al. (2007) employed multiple surrogates such as regression and interpolating local surrogates to provide a diversity of approximation models in a multi-surrogates assisted memetic algorithm.

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Gorissen et al. (2009) brought multiple surrogates to adaptive sampling. The objective is to be able to select the best surrogate model by adding points iteratively. Glaz et al. (2009) implemented a weighted-average approach in use of multiple surrogates. In their application they have found that at relatively little additional cost compared with optimizing with a single surrogate, multiple surrogates can be used to locate extrema of the objective function of their interest that would be overlooked if only a single approximation method was employed. Zhang et al. (2012) developed a hybrid surrogate modeling methodology that adaptively combines the favorable characteristics of different surrogate models including RBF and Kriging. The methodology generates different surrogate models (component surrogates), and weights aggregation of the estimated function value based on the local measure of accuracy of the individual surrogates.

In an attempt to put into test some of the developments that have shown to work mostly for analytically tractable problems and test bench functions, we assess the performance of two open source toolboxes which use ensemble surrogate strategies. These toolboxes are due to Müller and Piché (2011) that uses Dempster–Shafer theory to mix surrogate models, and Viana et al. (2013) that uses the multiple surrogates based on the square root of the prediction sum of squares for surrogate selection. These methods have not been used in the context of geo-engineering. So we assess the performance of these developments of uncertainty-laden models of heterogeneous reservoirs that adds to the complexity of the models. Also we apply two different optimization strategies to search for the optimal solution.

2. Model description, uncertainty and optimization problem

2.1. Governing equations

The water injection process into the oil reservoir is considered herein with assumptions of an immiscible and incompressible multiphase fluid flow with unit formation volume factor for oil and water. Gravity and capillary effects are neglected. The problem is described and sequentially solved by Darcy's law ($v_t = -\mathbf{K}\lambda_t(S_w)\nabla p$ in Ω), mass conservation equation ($\nabla\cdot v_t = q$) and the transport equation ($\varphi\frac{\partial S_w}{\partial t} + \nabla\cdot[v_t f_w(S_w)] = q_w$), where $v_t = v_o + v_w$ is the total Darcy velocity [m^3/day] of the engaging fluids (oil and water phases denoted by subscripts o and w, respectively), q represents the volumetric total source and sink contributions [m^3/day] of oil and water phases from the wells and boundary conditions. Also, $\mathbf{K}$ [mD] is the tensor of absolute permeability, $\lambda_t(S_w) = \lambda_o(S_w) + \lambda_w(S_w)$ is the total mobility and is a function of water saturation, S_w. The fluid pressure, p [atm], is, in the absence of capillarity, equal to oil and water phase pressures, p_o and p_w. Finally Ω is the problem domain.

In the transport equation, φ [–] is the porosity of the porous medium, $f_w(S_w)$ [–] is the fractional flow function of water defined by $f_w(S_w) = \lambda_w/\lambda_t$. The phase mobilities ($\lambda_o$ and λ_w) are herein modeled by polynomial water and oil relative permeability curves, $k_{ro}(S_{wD}) = k_{ro,\max}(1 - S_{wD})^{n_o}$ and $k_{rw}(S_{wD}) = k_{rw,\max}(S_{wD})^{n_w}$ and constant phase viscosities, μ_o and μ_w, as $\lambda_w(S_w) = k_{rw}(S_{wD})/\mu_w$ and $\lambda_o(S_w) = k_{ro}(S_{wD})/\mu_o$, where $S_{wD} = (S_w - S_{wc})/(1 - S_{or} - S_{wc})$. In these relations n_o and n_w are exponents of the polynomials controlling curvature of the curves, S_{wD} is the normalized water saturation that varies between zero and one as opposed to the water saturation that varies between S_{wc} (connate water saturation) and $1 - S_{or}$ where S_{or} is the oil residual saturation.

The above equations are solved with the open-source MATLAB Reservoir Simulation Toolbox (Lie et al., 2012).

2.2. Geological model

2.2.1. Two dimensional model

The two dimensional geological model used in this work is 3000 m × 3000 m × 1 m long in x, y and z directions representing a thin horizontal reservoir. The gridblocks are 50 m × 50 m × 1 in length, width and height respectively so that the number of gridblocks is 60 × 60. The boundaries are assumed fully closed and the reservoir is fully saturated with oil. The porosity of the model is a constant value of 0.2. The water and oil viscosities are 1.0×10^{-3} Pa s and 10.0×10^{-3} Pa s. The water and oil surface densities are 1014 and 859 kg m^{-3}. The relative permeabilities of oil and water are represented by quadratic polynomials ($n_o = n_w = 2$) and $k_{ro,\max} = k_{rw,\max} = 1$ and capillary pressure is ignored and the initial water saturation is set to zero.

The permeability is assumed uncertain but exhibiting, in two separate cases, the features of either of the following geo-environmental landscapes: a shale-dominant reservoir with multiple narrow diagonal intersecting channels with 45° orientation (denoted hereafter simply by Model 2D-a) and a sandstone reservoir crisscrossed with a multitude of lateral shale streaks (Model 2D-b).

In order to generate realizations of different permeability fields, S-GeMS (the Stanford Geostatistical Modeling Software available at http://sgems.sourceforge.net) is used. S-GeMS provides algorithms for multiple-point geostatistics. A review of multiple-point geostatistics is conducted by Hu and Chugunova (2008) and there are numerous subsurface modeling applications of it in literature (e.g., Ronayne et al., 2008; Mariethoz et al., 2010; Mariethoz and Kelly, 2011). One such algorithm is FILTERSIM (Zhang et al., 2006; Wu et al., 2008) that is used to build the image or numerical model by conditioning to local data patterns using a prior structural model given under the form of a visually explicit training image (Zhang et al., 2006). Reproducing geological shapes based on a training image by multiple-point geostatistics is more realistic than the traditional two-point geostatistics that utilizes variogram models to characterize the spatial structure of data as the variograms often cannot capture curvilinear structures and shapes of geological bodies such as channels (Journel, 1993; Strebelle, 2000).

The training image here is an image of a diagonally channelized permeability field (Model 2D-a) or a shale populated sandstone (Model 2D-b). The training image serves as prior knowledge of the geology of the reservoir. Figs. 1 and 2 show the six realizations of the absolute permeability obtained by unconditional continuous FILTERSIM simulation using S-GeMS for the two cases of permeability considered in this work to introduce uncertainty.

The water injection is performed by four injection wells (I1, I2, I3 and I4) at the corners of the reservoir and one production well in the center of the reservoir (P1) as shown in Fig. 1.

2.2.2. Three dimensional model

We use an ensemble version (with 100 realizations) of the Egg Model (Jansen et al., 2013) for the three dimensional example and we refer to it as Model 3D. The model has 60 × 60 × 7 grid cells of which 18,553 cells are active leaving an egg-shaped model after eliminating the inactive cells. The gridblocks are 8 m × 8 m × 4 m in length, width and height respectively. The porosity is 0.2. Oil and water viscosities are 5.0×10^{-3} Pa s and 1.0×10^{-3} Pa s. The water and oil surface densities are 1000 and 900 kg m^{-3}. For the relative permeabilities of oil and water, $n_o = 4$, $n_w = 3$ and $k_{ro,\max} = 0.8$, $k_{rw,\max} = 0.75$ and $S_{wc} = 0.2$, $S_{or} = 0.1$. Capillary pressure is ignored and the initial water saturation is set 0.1.

The permeability fields (Fig. 3a) demonstrate channelization with strong vertical correlation. There are no aquifer or gas cap in the model, the primary production is neglected, and the production