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Surrogate based optimal waterflooding management

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ABSTRACT

In this work we solve the optimal waterflooding management problem using as design variables the rates allocated to each injector and producer well under different operational conditions. The duration of each control cycle may also be optimally controlled. The objective function is the net present value. As the cost of numerical simulation can be very high it is generally not feasible to couple the simulator directly to the optimizer. Therefore a cheap surrogate model is used to capture the main trends of the objective and constraint functions. In this work we adopt Kriging data fitting approximation to build surrogate models to be used in the context of local optimization.

The Sequential Approximate Optimization (SAO) strategy is used to solve the problem as a sequence of local problems. A trust region based framework is employed to adaptively update the design variable space for each local optimization. Sequential Quadratic Programming (SQP) is the algorithm of choice for the local problems. For illustrative purposes two reservoir problems are presented. The first is a small problem, with three wells, used to tune algorithmic parameters. The second is a medium sized reservoir, with 12 wells, used to demonstrate the potentials of the proposed method. The technique proved to be accurate and its performance confirms the efficient regularization of simulator numerical noise. It was successful in identifying wells that should be late started or shut-in before the end of the concession period and in handling different kinds of production strategies. Increase in operation flexibility resulted in NPV improvement. Cycle duration variables proved to be useful in decreasing the number of design variables while maintaining recovery efficiency.

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1. Introduction

In Oil Reservoir Engineering applications one problem of great interest is the dynamic optimization of production scheduling, considering constraints at field total rate meaning that all wells share common injection and production units. The waterflooding optimal management problem, which is by far the most commonly used method to improve oil recovery, is studied here. The objective is to maximize the economic return of the field using as controls the rates of injector and producer wells.

There is a vast literature on the dynamic rate allocation optimization for waterflooding. One may classify the methods according to the degree of intrusion into the simulator code. The highly intrusive methods make use of the adjoint technique to compute the gradient of the objective function (Jansen, 2011), and are among the most efficient methods (Brouwer and Jansen, 2004; Sarma et al., 2008; Chen et al., 2010, 2012). Adjoint methods require a large programming effort to be implemented and are not available in all commercial simulator codes at the present time. The semi-intrusive methods make use of reduced order models (Cardoso and Durlofsky, 2010; He et al., 2011), or time of flight concept in streamline simulators to equalize water breakthrough in groups of producer wells (Alhuthali et al., 2009). Finally the non-intrusive methods use the simulator as a black-box and are purely data driven. Algorithms typically use evolutionary techniques (Oliveira, 2006; Almeida et al., 2010; Souza et al., 2010), pattern search methods (Asadollahi et al., 2009) and surrogate based methods (Queipo et al., 2002; CMOST, 2012). Another class of derivative-free algorithms use approximate gradients of the objective function based on stochastic methods (Wang et al., 2009) and ensemble methods (Chen and Oliver, 2010), which may be corrected by additional finite difference computations (Xia and Reynolds, 2013) or be incorporated into a quadratic interpolation model (Zhao et al., 2011). Additional discussion may be found in Conn et al. (2009).

The method considered herein is of the non-intrusive kind. As the numerical simulation has high computational cost it cannot be directly coupled to the optimization algorithm. We use Kriging data fitting approximation approach to overcome the above mentioned problem (Giunta, 2002; Forrester et al., 2008). From a proper choice of a design of experiments (DOE) scheme, followed by the evaluations of the true (high fidelity) function at the

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samplings, a Kriging predictor is built in order to evaluate the functions at untried points during the optimization algorithm iterations. This surrogate model is similar to that employed by Queipo et al. (2002) except that while they used a global, box constrained, optimization technique, we adopt Sequential Quadratic Programming (SQP) (Powel, 1978), which is a local search type algorithm, and any general constraints may be included in the problem formulation. This is embedded here in an interactive procedure named Sequential Approximate Optimization (SAO) (Alexandrov et al., 1997). A trust region based method is used to update the design variable space for each local optimization subproblem. This globalization technique is being used by other researchers in the waterflooding optimization context (Chen et al., 2012).

Usually the concession period is subdivided into a number of control cycles, whose switching times are fixed in time, and using as design variables the well rates in each cycle. Oliveira and Reynolds (2013) present a hierarchical procedure to determine appropriate number and duration of control cycles. The well by well approach is based on criteria for refining/coarsening of control cycles based on gradients of the objective function and differences between consecutive well controls at each well. If gradients are not available only the latter criterion is applicable, in which case the merging potential may be affected if optimal controls tend to be rough.

In this work the times of switching of control cycles may also be used as controllable variables. This approach naturally considers possible interrelationships between wells and also the influence of imposed constraints. Flexibility in management is increased which leads to a decrease in the total number of variables for similar recovery efficiency.

The present work compares solutions obtained using different operational strategies of production. Full capacity operation solutions, where both injection and production lines are operated at their limit capacities, are compared with more flexible operational constraints, where some wells may be shut-in before the end of the concession period while others may be started after the beginning of operations.

Two example problems are presented. The first is a small reservoir, with three wells, used for the conduction of extensive parametric studies on different surrogate construction approaches, tuning of SAO parameters, and reservoir operation strategies. The second example is a medium sized reservoir, with 12 wells, solved considering the main results of the parametric study.

2. The waterflooding problem

2.1. Definition

Waterflooding is the most commonly used method to improve oil recovery and maintain the reservoir at a proper pressure level. Optimization techniques can be applied to improve waterflooding sweep efficiency through management of the propagation of the water front. In this sense, one problem of great interest is the dynamic optimization of producing scheduling, leading to optimal rate allocation to the injectors and producers. In this problem, the net present value (NPV) is considered as the objective function and the field total rates are the constraints.

2.2. Formulations

Mathematically the waterflooding problem can be formulated as follows:

$$\begin{aligned}
&\text{Maximize NPV } = f(\mathbf{q}) = \sum_{t=1}^{n_t}\left[\frac{1}{(1+d)^{\tau_t}}F(\mathbf{q}_t)\right]\\
&\text{subject to : } \sum_{p\in P} q_{p,t} \le Q_{l,max}, \quad t=1\ldots n_t\\
&\sum_{p\in I} q_{p,t} \le Q_{inj,max}, \quad t=1\ldots n_t\\
&q^l_{p,t} \le q_{p,t} \le q^u_{p,t}, \quad p=1\ldots n_w, \quad t=1\ldots n_t\\
&\sum_{p\in P} q_{p,t} \le \sum_{p\in I} q_{p,t} \le \delta \sum_{p\in P} q_{p,t}, \quad t=1\ldots n_t
\end{aligned} \tag{1}$$

where $\mathbf{q}=[\mathbf{q}_1^T\ \mathbf{q}_2^T\ldots\mathbf{q}_{n_t}^T]^T$ is the vector of well rates for all control cycles; $\mathbf{q}_t=[q_{1,t}\ldots q_{n_w,t}]^T$ is the vector of well rates at control cycle t; $q_{p,t}$ is the liquid rate of well p at control cycle t; n_t is the total number of control cycles; and n_w is the total number of wells. In the objective function d is the discount rate and τ_t is the time at the end of the tth control cycle. The cash flow at control cycle t, which represents the oil revenue minus the cost of water injection and water production, is given by

$$F(\mathbf{q}_t)=\Delta\tau_t\left[\sum_{p\in P}(r_o q^o_{p,t}-c_w q^w_{p,t})-\sum_{p\in I}(c_{wi}q_{p,t})\right] \tag{2}$$

where $\Delta\tau_t$ is the time size of the tth control cycle; P and I are the sets of production and injection wells, respectively; $q^o_{p,t}$ and $q^w_{p,t}$ are the average oil and water rates at the pth production well at tth control cycle; r_o is the oil price; c_w and c_{wi} are the costs of producing and injecting water.

$Q_{l,max}$ is the maximum allowed total production liquid rate and $Q_{inj,max}$ is the maximum allowed total injection rate of the field. Superscripts l and u denote respectively the lower and upper bounds of design variables. Superscripts o and w denote respectively oil and water phases. The last constraint requires that, for all cycles, the total injection rate belongs to an interval that goes from the total production rate to δ times this value, where $\delta \ge 1$ is the over injection parameter. This is a more general form of the so-called voidage replacement constraint used by many researchers as a means to maintain the reservoir properly pressurized (Brouwer and Jansen, 2004; Naevdal et al., 2006; Van Essen et al., 2009; Asadollahi, 2012). Although reduction of the voidage replacement fraction at the end of the production period may improve NPV (Lorentzen et al., 2009) this practice may produce undesirable effects (Asadollahi and Naevdal, 2010). This constraint is not a mandatory part of the optimization process and may be deleted from the formulation if the user deems appropriate.

The commonly used approach to these problems is to subdivide the concession period into a number of control cycles, n_t, whose switching times are fixed (see Fig. 1). The design variables are the well rates in each control cycle. Let well rates be scaled by their respective maximum allowable field rates:

$$x_{p,t}=\frac{q_{p,t}}{Q_{l,max}},\ \ p\in P; \quad x_{p,t}=\frac{q_{p,t}}{Q_{inj,max}},\ \ p\in I \tag{3}$$

Design variables, $x_{p,t}$, are then the allocated rate for well p at time at cycle t. We consider two alternative formulations for this problem: full capacity operation (FCO) and non-full capacity operation (NCO) (Horowitz et al., 2010). In FCO the sum of both production and injection rates are exactly at maximum field total rates:

$$\begin{aligned}
&\text{Maximize NPV } = f(\mathbf{x}) = \sum_{t=1}^{n_t}\left[\frac{1}{(1+d)^{\tau_t}}F(\mathbf{x}_t)\right]\\
&\text{subject to : } \sum_{p\in P} x_{p,t} = 1, \quad t=1\ldots n_t\\
&\sum_{p\in I} x_{p,t} = 1, \quad t=1\ldots n_t\\
&x^l_{p,t} \le x_{p,t} \le x^u_{p,t}, \quad p=1\ldots n_w, \quad t=1\ldots n_t
\end{aligned} \tag{4}$$

where $\mathbf{x}=[\mathbf{x}_1^T\ \mathbf{x}_2^T\ \cdots\ \mathbf{x}_{n_t}^T]^T$ is the vector of scaled well rates for all cycles; $\mathbf{x}_t=[x_{1,t}\cdots\ x_{n_w,t}]$ is the vector of scaled well rates for cycle t. Notice that the number of design variables for both injection and production wells may be decreased by one. The total number of

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