SPE 142043

Using Multiscale Regularization to Obtain Realistic Optimal Control Strategies

Yuanyuan Shuai, Christopher D. White, Hongchao Zhang and Ting Sun, Louisiana State University

This paper was prepared for presentation at the SPE Reservoir Simulation Symposium held in The Woodlands, Texas, USA, 21-23 February 2011.

Abstract

Smart well technology is attracting increasing attention because it promises to add operation flexibility and potentially increases oil recovery. However, it remains difficult to find the best strategy for production optimization. One challenge is to find a good optimization algorithm, as some optimization algorithms require prohibitive work to compute the gradients of the objective function with respect to the well controls. These methods also require access to the simulator code, which makes them difficult to use with commercial software. Another challenge is to find a reasonable frequency for well control adjustment: adjusting well controls too frequently imposes unrealistic control burdens on operations, increasing well management cost. Moreover, high–frequency control adjustment increases the risk of optimization algorithms being trapped at local optima as the problem is more under–determined. On the other hand, excessively low–frequency control adjustment may not truly optimize oil recovery.

To address these issues, two simulator-independent optimization algorithms were investigated: ensemble-based optimization (EnOpt) and bound optimization by quadratic approximation (BOBYQA). Multiscale regularization was applied to both to find appropriate frequencies for well control adjustment. In a synthetic case study, if multiscale regularization was not used, then EnOpt converged to a higher net value of production than BOBYQA —even though BOBYQA uses second order Hessian information (EnOpt uses first order gradients). BOBYQA performed comparably only if multiscale regularization was used. After multiscale regularization, both methods obtained net value of production (NVP) that equalled or exceeded unregularized optimization, with simpler well control strategies and convergence in fewer iterations.

Introduction

Since the first smart well was installed at Saga's Snorre Tension Leg Platform in North Sea in 1997, more than 300 smart well systems have been installed worldwide (Gao, Rajeswaran, and Nakagawa 2007). The benefits of smart wells have been demonstrated in theoretical studies and practical applications (Brouwer et al. 2001; Jansen et al. 2002; Ramakrishnan 2007; van Essen et al. 2009; Meshioye et al. 2010; van Essen et al. 2010). These benefits can summarized as two types: (1) for highly heterogeneous reservoirs, smart wells can help avoid early water or gas breakthrough from high permeability zones, and (2) for multilateral wells (or monobore wells with multiple segments), smart wells provide flexibility to control each branch (or segment) of the well independently. Smart wells can do this because, unlike conventional wells, smart wells have permanent downhole sensors and controls. Those sensors provide realtime rates, pressures and temperatures; the control valves allow control of flow in each reservoir interval. The data feedback and inflow control valves (ICVs) are the key components of smart well systems. Based on the feedback, the downhole control valves are adjusted to suppress unwanted fluid production and increase oil recovery.

There are two approaches for using smart well technology, reactive control and proactive control (Aitokhuehi 2004; Yeten, Durlofsky, and Aziz 2002; Addiego-Guevara, Jackson, and Giddins 2008). With reactive control, the ICVs are adjusted either by continuously reducing the interval rate or closing the interval entirely to control excessive water or gas production. Proactive control is also called defensive control. With this strategy, the valve settings are optimized a priori using a predictive reservoir model.

Optimization algorithms can be used to find the optimum valve settings. These methods can be categorized into two classes, gradient–free methods and gradient methods. Gradient–free methods do not rely on gradient information to guide the optimization search. Their primary benefits are their potential to find the global optimum and the ability to handle discrete design variables. Because they are capable of discrete parameter optimization, gradient–free methods are also used in well placement optimization (Onwunalu and Durlofsky 2010). A considerable disadvantage of gradient–free methods is that they

require more function evaluations than gradient methods and converge slowly. For instance, Isebor (2009) compared gradient–free methods (including a genetic algorithm, general pattern search, and Hooke-Jeeves direct search) with a gradient method (sequential quadratic programming) for constrained production optimization. Isebor found that the gradient–free methods tend to be about an order of magnitude slower than the gradient method with adjoint–computed gradients. To improve the efficiency of gradient–free methods, one should combine them with a local optimization method. Harding, Radcliffe, and King (1996) showed the combination of a genetic algorithm with sequential quadratic programming for local search outperforms the "pure" genetic algorithm. This was also observed by Isebor (2009).

In contrast, gradient methods take advantage of the gradient information to guide their search. Despite their inability to guarantee a global optimum, these methods converge much faster than gradient–free optimization. Common methods of this type used in production optimization are steepest ascent (Chen, Oliver, and Zhang 2009), conjugate gradient (Chaudhri et al. 2009), and sequential quadratic programming (Isebor 2009).

For gradient optimization, two approaches can be used to compute the gradients of objective function with respect to well control variables. One approach is to obtain the gradients using the adjoint equation. The other approach is to approximate the gradients using methods such as finite difference perturbation, simultaneous perturbation stochastic approximation, or EnOpt. Among all these methods, the adjoint method is the most robust and therefore the most efficient. For example, Chen et al. (2010) found that the adjoint method converges in less than 50 simulation runs if it was used to optimize production for a Brugge case with about 3600 well control variables. However, few commercial softwares provide adjoint gradients, and computing them requires detailed knowledge of the underlying simulator formulation. Unlike the adjoint method, approximate gradient methods can treat the simulator as a "black box." However, extra function evaluations — here, simulation runs — are required to approximate the gradients.

We compare two simulator–independent optimization methods, ensemble-based optimization (EnOpt) and bound optimization by quadratic approximation (BOBYQA). The application of multiscale regularization to find the best well control frequency is also tested on these two methods. Multiscale regularization aims to avoid too–frequent control adjustment by adding well control parameters hierarchically.

Optimization Formulation and Methods

Objective function. In production optimization, net present value (NPV) is generally used as the objective function that can be maximized by adjusting the well control vector (Wang, Li, and Reynolds 2009; Chen, Oliver, and Zhang 2009; Chaudhri et al. 2009). Assuming no cost for water injection, following Chaudhri et al. (2009), the formula for calculating NPV of a single two-phase (oil/water) reservoir model is given as:

$$g(X) = \sum_{i=1}^{N_t} \frac{v_o Q_{o_i}(X) - v_w Q_{w_i}(X)}{(1+r_\tau)^{\frac{t_i}{\tau}}}, \tag{1}$$

where, X is the N_x–long vector of control variables, and N_t is the number of control time steps; v_o and v_w are oil price and water disposal cost, respectively. The increments of oil and water production over time step i are Q_{o_i} and Q_{w_i}; r_τ is the discount rate, and t_i is cumulative time at time step i. The objective function $g(X)$ gives NPV as a function of the well controls X. If the discount rate is set to zero, the denominator in Eq. 1 is unity and the objective function can be simplified to

$$g(X) = \sum_{i=1}^{N_t} \left[v_o Q_{o_i}(X) - v_w Q_{w_i}(X) \right]. \tag{2}$$

The objective function $g(X)$ in Eq. 2 is the net value of production (NVP), as no discount factor is considered.

Ensemble Optimization. EnOpt was first introduced in production optimization by Nwaozo (2006) and further investigated by Chen, Oliver, and Zhang (2009), Wang, Li, and Reynolds (2009), and Chaudhri et al. (2009). EnOpt can be applied for the optimization of a large number of well control settings. In addition, EnOpt can account for uncertain reservoir models without increasing the number of optimization parameters if an ensemble of reservoir models is available (as for EnKF history matches).

EnOpt (Chen, Oliver, and Zhang 2009) uses the steepest ascent method to iteratively update the well control vector X, and at each iteration uses a perturbed ensemble to approximate the gradients. At iteration l, N_e samples of well control vectors $X_{l,j}$ are randomly generated following a Gaussian distribution, N_e simulations are run, and then the net value of production $g(X_{l,j})$ is evaluated for all $j \in \{1 \dots N_e\}$ using Eq. 2; N_e is the number of models in the ensemble. Following Chen, Oliver, and Zhang (2009), the gradients of objective function NVP with respect to well controls can be approximated as

$$G_l^T \approx C_{X_l}^{-1} C_{X_l, g(X_l)}, \tag{3}$$

with

$$C_{X_l,g(X_l)} = \frac{1}{N_e - 1}\sum_{j=1}^{N_e}(X_{l,j} - \bar{X}_l)(g(X_{l,j}) - \bar{g}(X_l)), \tag{4}$$

and

$$C_{X_l} = \frac{1}{N_e - 1}\sum_{i,j=1}^{N_e}(X_{l,i} - \bar{X}_l)(X_{l,j} - \bar{X}_l)^T. \tag{5}$$

In Eq. 3, G_l is the vector of the gradients at iteration l. C_{X_l} is the covariance matrix of the well control variables X_l. $C_{X_l,g(X_l)}$ is the cross-covariance between well control variables $X_{l,j}$ and objective function $g(X_{l,j})$. In Eq. 4 and Eq. 5, $\bar{X}_l$ and $\bar{g}(X_l)$ indicate the mean values of well controls and the objective function for the ensemble at iteration l. They are

$$\bar{X}_l = \frac{1}{N_e}\sum_{j=1}^{N_e} X_{l,j},$$

and

$$\bar{g}(X_l) = \frac{1}{N_e}\sum_{j=1}^{N_e} g(X_{l,j}).$$

The steepest ascent equation for updating control variables X is

$$X_{l+1} = X_l + \frac{1}{\alpha_l} C_{X_l} C_{X_l} G_l^T, \tag{6}$$

where α_l is a tuning parameter to determine step size in the search direction at iteration l. Because the cross-covariance estimated using a perturbed ensemble may suffer from spurious correlation when the ensemble size is not sufficiently large, Chen, Oliver, and Zhang (2009) suggest using a matrix product of the covariance matrix of the control variables $R_X = C_X C_X$ for localization and smoothing.

After substituting Eq. 3 to Eq. 6, the steepest ascent method used for ensemble optimization becomes

$$X_{l+1} = X_l + \frac{1}{\alpha_l} C_{X_l} C_{X_l,g(X_l)}.$$

Trust–Region Optimization. BOBYQA is a package of Fortran subroutines written by Powell (2009). It is an iterative algorithm for solving bound–constrained problem in which the objective function can be treated as a black box. The BOBYQA method (Powell 2009) applies a trust region optimization algorithm for bound–constrained nonlinear optimization. This method does not require derivative information for the objective function, nor does it explicitly approximate the derivatives. Instead, at each iteration it builds a local quadratic model $Q(X)$ of the objective function $g(X)$ by multivariate interpolation in combination with trust region techniques. The quadratic model employs the form,

$$Q(X + d) = Q(X) + d^T \bigtriangledown Q(X) + \frac{1}{2} d^T \bigtriangledown^2 Q(X) d,$$

which is solved by conditioning

$$Q(X_i) = g(X_i),\ \forall i \in \{1 \dots m\},$$

where $m \in \{(n+2) \dots (2n+1)\}$ and n is the total number of control variables. In our numerical experiments, $m = n + 2$ function evaluations are used to build the quadratic model $Q(X)$.

The algorithm used by BOBYQA is an iterative algorithm that uses the least Frobenius norm updating strategy. At each iteration, we solve the following optimization problem

$$\begin{aligned} \min \quad & \|\nabla^2 \ell_t\|_F \\ s.\,t. \quad & \ell_t(X^+) = 1,\ \ell_t(X) = 0, X \in \mathbf{X} \setminus X_t, \end{aligned} \tag{7}$$

where ℓ_t is a second order polynomial which needs to be determined, $\mathbf{X}$ is the current set of interpolation points, X^+ is a new point added to $\mathbf{X}$ and X_t is a point deleted from $\mathbf{X}$ (Powell 2009). For an $n \times n$ matrix A with entries $a_{ij}, i, j \in \{1 \dots n\}$, the Frobenius norm is

$$\|A\|_F = \sqrt{\sum_{i,j=1}^{n} a_{ij}^2}\ .$$

Then, the new model $Q^+(X)$ is updated by

$$Q^+(X) = Q(X) + \{g(X^+) - Q(X^+)\}\ell_t(X),$$

where $\ell_t(X)$ is the solution of (Eq. 7). Eq. 7 has a closed form solution, which can be computed by solving a linear system (Powell 2009).

Hence, only on the order of n function evaluations could be used for building the quadratic model, whereas normally $(n+1)(n+2)/2$ function evaluations are required for building a fully quadratic model. Global convergence as well as the good local sampling for building the quadratic model are guaranteed by trust region techniques. Recent research (Moré and Wild 2009) in the computational optimization community indicates this trust region model method performs better than other optimization methods without explicit gradient computations.

Comparing with EnOpt, for small scale problems (less than a hundred unknowns) we would expect BOBYQA to converge faster because it extracts local second order Hessian information, whereas EnOpt only uses first order gradient information. Moreover, at each iteration, it requires only one new function evaluation to update the local quadratic model whereas EnOpt requires an ensemble of function evaluations to update the gradients. However, BOBYQA is limited to medium scale optimization problems (a few hundreds of variables), because at least $n+2$ function evaluations are needed for building the first quadratic model; this is unacceptable for large scale problems (thousands of variables) with expensive function evaluations.

Multiscale Regularization. In production optimization, specifying the frequency of well control adjustment is a challenge. On one hand, high–frequency control adjustment imposes unrealistic control burdens on operations, increasing well management cost. In addition, high–frequency control implies many control variables, and many degrees of freedom increase the risk of an optimization algorithm being trapped at local optimum, as the problem is less well–determined. Moreover, some optimization algorithms can be computationally infeasible when the number of unknowns is large. On the other hand, excessively low–frequency control adjustment may not truly optimize oil recovery.

Multiscale regularization provides a way to address this problem. It starts optimization from the coarsest control scale (and thus, with the fewest number of control parameters) and refines successively using the coarse-scale solution as the initial guess of controls for next finer scale optimization. The refining process is terminated when no further improvement on the objective function is obtained.

In this paper, we test the performance of ordinary multiscale regularization with the EnOpt and BOBYQA optimization methods. Lien et al. (2008) used adaptive multiscale regularization with an adjoint method for production optimization. Their method needs fixed, fine–scale gradients of the objective function as indicators to guide the refinement. We use ordinary multiscale regularization rather than gradient-based adaptive multiscale regularization for two reasons. First, the gradients calculated by both EnOpt and BOBYQA are approximate rather than true gradients, so that gradient adaptive multiscale regularization may not outperform ordinary multiscale regularization; we observed no improvement in our numerical experiments. Second, computing the fine-scale gradients at each refinement stage is expensive for BOBYQA method, requiring at least $n+2$ function evaluations to build the quadratic model.

The step-wise procedure for ordinary multiscale regularization is:

1. At scale $l = 1$ (the coarsest scale), one well control is used for each well; the number of unknowns is equal to the number of wells. The time step is set equal to the production (optimization) period. Initial values are assigned to each well control.

   START: DO WHILE LOOP (check stop criterion, see if further refinement improves NVP)

2. Find optimum solution for scale l using EnOpt or BOBYQA

3. $l = l + 1$. Reduce time step by a factor of 2, and increase the number of control parameters by a factor of 2. Use the solution from step 2 as the initial well control for this scale.

   END: DO WHILE LOOP

As both EnOpt and BOBYQA are iterative methods, in addition to the outer "DO WHILE" loop used for refinement, there is an inner loop for well control updating at each scale l, which is not shown here. The change in NVP is also used as the stop criterion for the inner loop. The stop criterion for the inner loop is not kept constant. Instead, it is decreased as the scale is refined, because convergence at the coarse scale takes many simulation runs while NVP is only slightly increased.

Test Case

The EnOpt and BOBYQA optimization methods are applied to a simple–but–interesting synthetic test case. Optimization is done with and without multiscale regularization, and the results for all cases are compared.

Case Description. We consider a two-dimensional two-phase synthetic reservoir model. It has 45 × 45 × 1 grid blocks with a uniform grid block size of 50 ft × 50 ft × 15 ft. To add heterogeneity, the reservoir model is "channelized" with three uniform high–permeability zones (5 D) and a low–permeability back ground (80 mD; **Fig. 1**). Reservoir porosity is uniform and equal to 0.2. Nine producers and four injectors are located in a repeated five-spot well pattern, with three producers and two injectors positioned at high permeability channel and others positioned at the low permeability background. This configuration is chosen to induce intuitively clear challenges in well control optimization (Discussion, later).

During the water flooding process, water is injected at 900 stb/day for each injector with a total injection rate of 3600 stb/day. Only fluid production rates for producers are considered as control variables for the NVP optimization. The time frame for optimization is 960 days (32 months). The price of oil revenue is 80 $/bbl and the cost for produced water disposal is 5 $/bbl. The total fluid production rate constraint of 3600 stb/day is imposed for the producers.

Optimization Parameters. Before multiscale regularization, the time step for production optimization is 60 days. Thus, there are 16 control variables for each producer and 144 total unknowns. For multiscale regularized EnOpt and BOBYQA, the coarsest scale time step is 960 days, with one control variable for each producer. As regularization proceeds, the time step decreases by a factor of two whereas the total number of control variables increases by a factor of two for the next finer scale. The refinement is continued until the stop criterion is reached. An ensemble size of 30 is used for ensemble-based method. A nonoptimized case is used as a reference case, in which the total production rate is equally distributed among the producers (400 stb/day for each producer). If not specified otherwise, this is also the initial value used for the optimized scenarios discussed in the next section.

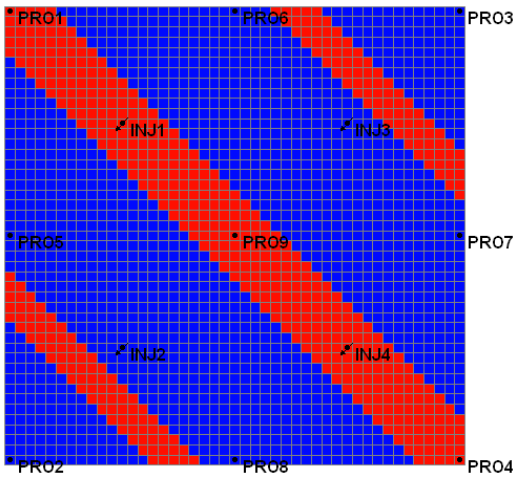
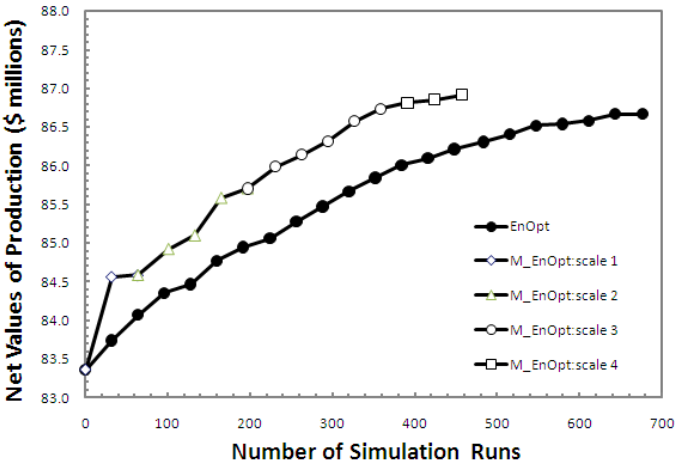
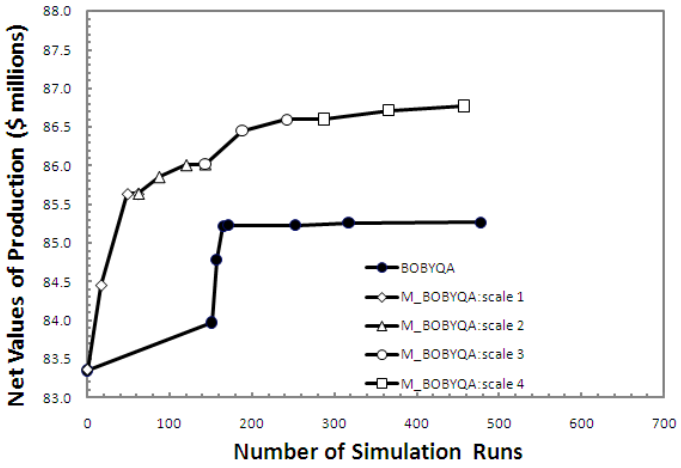


Figure 1: The permeability distribution of the channelized synthetic example: 5 D for three high permeability channels and 80 mD for the low permeability background.

Results. The optimized NVPs for EnOpt, BOBYQA, multiscale regularized EnOpt and multiscale regularized BOBYQA range from 85.3 to 86.9 million dollars (**Fig. 2**). All optimized cases have higher NVPs compared with the nonoptimized case (NVP with constant rates). Multiscale regularized EnOpt (Fig. 2(a), upper curve) obtains the highest NVP among all these methods. Multiscale regularized BOBYQA (Fig. 2(b), upper curve) has a similar NVP to EnOpt (Fig. 2(a), lower curve), but with faster convergence. The BOBYQA (Fig. 2(b), lower curve) method is not as efficient as other methods. With $n+2$ ($n = 144$ before multiscale regularization) function evaluation runs to build the quadratic model, BOBYQA takes less than 20 simulation runs to converge because it uses second order gradients. However, it converges to a local optimum instead of the global one; for this particular system, BOBYQA may converge to a local optimum if the number of control variables is more than a hundred. In comparison, regularized BOBYQA has higher NVP even at the coarsest scale of reguarization (scale 1). For EnOpt, the effect of multiscale regularization is not as significant as for BOBYQA, but the convergence speed and NVP are improved slightly. Moreover, both multiscale regularized cases terminate at scale 4 with a total number of 72 (8 control variables × 9 wells) unknowns, which is 50% fewer than the total number of well controls (16 control variables × 9 wells = 144 unknowns) used in unregularized EnOpt and BOBYQA methods.



(a) EnOpt and multsicale regularized EnOpt



(b) BOBYQA and multsicale regularized BOBYQA

Figure 2: NVP as a function of number of simulation runs before and after multiscale regularization. Multiscale regularized methods converge to higher NVPs with fewer simulation runs and fewer control variables. (scale 1: 1 control variable for each producer each 960 days; scale 2: 2 control variables for each producer each 480 days; scale 3: 4 control variables for each producer each 240 days; scale 4: 8 control variables for each producer each 120 days; unregularized cases: 16 control variables for each producer each 60 days.)

Discussion

Improving Sweep Efficiency. In the nonoptimized case (**Fig. 3(a)**), water is breaking through to producers 1 and 4 as they are connected to injectors 1 and 4 by high permeability channel, leaving unswept regions due to permeability heterogeity. After optimization (Fig. 3(b) to Fig. 3(e)), water breakthrough for producers 1 and 4 are delayed by all optimization algorithms and the unswept area is reduced. In addition, multiscale regularization (Fig. 3(c) and Fig. 3(e)) reduces the unswept area for both EnOpt and BOBYQA.

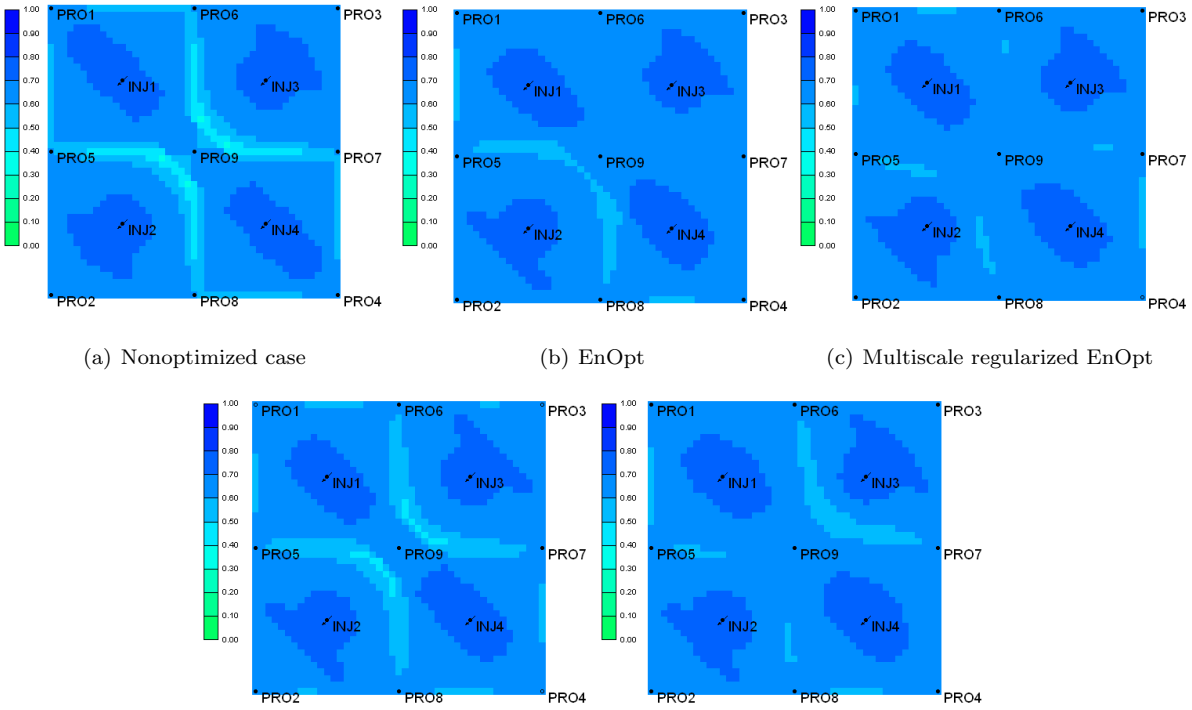
Sensitivity to Initial Controls. Because this problem is nonlinear, the optimization is nonunique and may be sensitive to initial guesses of the control vector. When different initial guesses are used with unregularized methods (**Table 1**), there is a significant effect on the controls and the net value of production (differences up to 1.61% for EnOpt and 2.09% for BOBYQA). Regularization allows all methods to converge to consistent, higher optima regardless of differences in the initial controls (differences less than 0.35% and 0.23% for regularized EnOpt and BOBYQA). This is important, because the initial controls may be difficult to specify for complex reservoir models. Three initial guesses used in Table 1 are:

- Initial 1 assigns the production rates from the coarsest scale of multiscale regularized BOBYQA optimization to the producers. For producers 1 to 9 these are 177, 249, 262, 206, 375, 887, 598, 413 and 433 stb/day, respectively.
- Initial 2 assigns 400 stb/day to each producer.
- Initial 3 uses the same production rates used as for initial 1, except the order of assignment is from producer 9 to 1. This initial estimate is farther from optimal than initial 1.

Table 1: The Effect of Initial Guesses on Optimized NVPs ($ millions) for Different Methods

Methods	Optimized NVP using initial 1	Optimized NVP using initial 2	Optimized NVP using initial 3	Difference (%)
EnOpt	86.8	86.7	85.4	1.61
BOBYQA	85.8	85.3	84.0	2.09
Multiscale regularized EnOpt	86.7	86.9	86.6	0.35
Multiscale regularized BOBYQA	86.6	86.7	86.5	0.23

Evolution of Controls. The changes of well controls as simulation runs are shown for producers 1 and 5 in **Fig. 4** and **Fig. 5**. Producer 1 is located in a high permeability channel whereas producer 5 is located in the low permeability background.



(a) Nonoptimized case (b) EnOpt (c) Multiscale regularized EnOpt

(d) BOBYQA (e) Multiscale regularized BOBYQA

Figure 3: Water saturation at the end of 32 months before and after multiscale regularization. Areas with darker blue have been swept. Thus, the relatively large extents of the cyan hues in the nonoptimized case indicate lower recovery. EnOpt improves recovery (less cyan); BOBYQA performs comparably only if multiscale regularization is used.

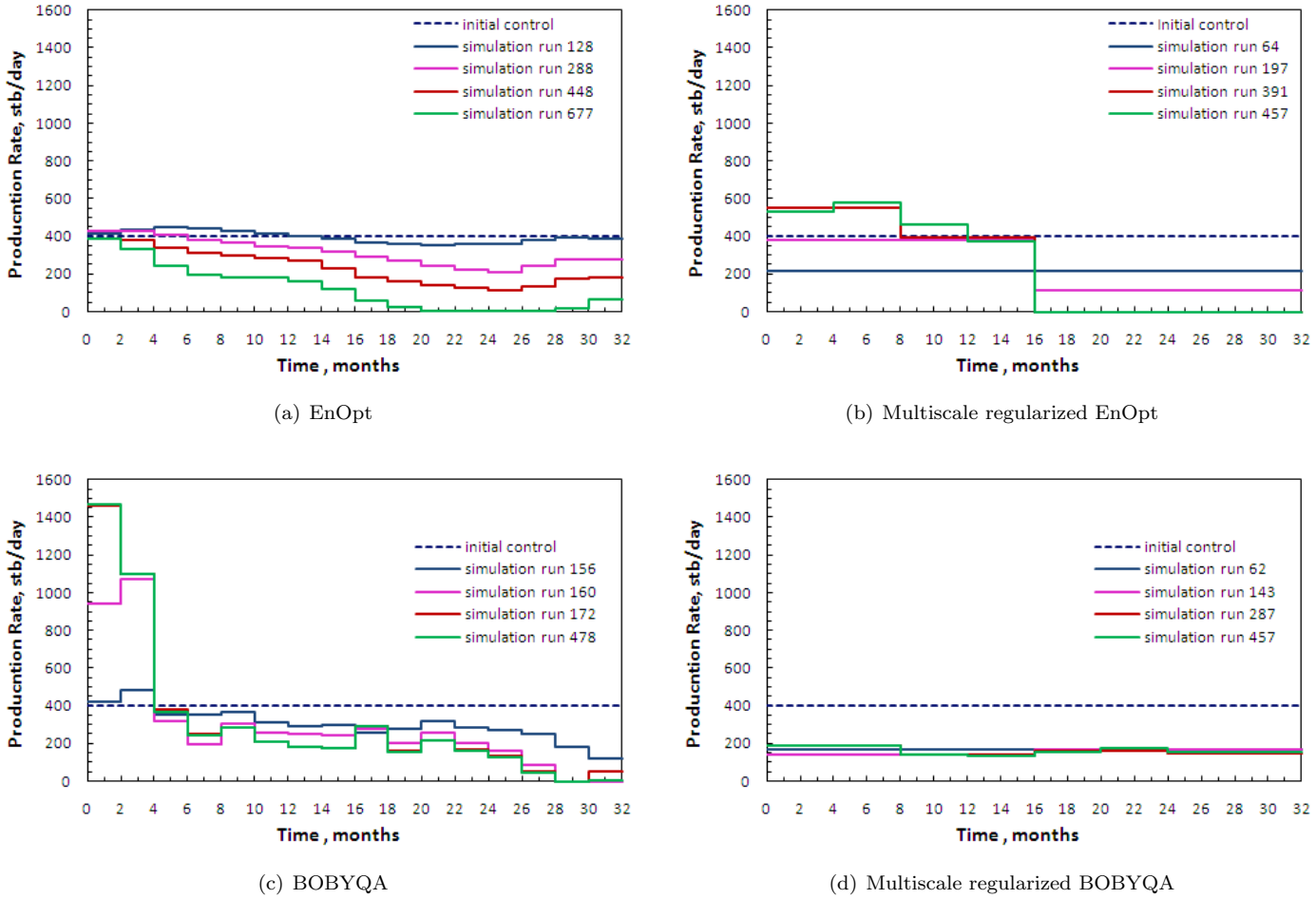
For both EnOpt and BOBYQA, multiscale regularized algorithms tend to have simpler control strategies but with more sudden changes in most cases (compare right figures in Fig. 4 and Fig. 5 with their left figures). Instead of specifying a fixed resolution and optimizing a large control set initially, multiscale regularization optimizes from a low resolution and sequentially increases resolution to avoid high–dimensional local optima. Apparently (Fig. 4(b), Fig. 4(d), Fig. 5(b) and Fig. 5(d)), the coarse scale optimizes in some average sense, providing a good initial estimate for next finer scale.

Optimized well control trends from most methods are similar (**Fig. 6**). Because producer 1 is connected to injector 1 by a high permeability channel, the optimized controls from EnOpt, multiscale regularized EnOpt and BOBYQA tend to be higher at the beginning of production due to the better transmissibility, and then decrease gradually to reduce water production after water breakthrough (Fig. 6(a)). Similarly, as producer 5 is positioned at the low permeability background, it takes much longer for water to breakthrough comparing with producer 1. Therefore, this objective function is less sensitive to producer 5 than producer 1. But to satisfy the total liquid production rate constraints (3600 stb/day), the optimized well controls from multiscale regularized EnOpt, BOBYQA and multiscale regularized BOBYQA increase at later time because of the rate reduction from wells (e.g., producer 1) in the high permeability channel (Fig. 6(b)).

Nonuniqueness and Optimality. The optimized control trends from most methods are similar. However, some well control trends from different methods are different even though they have similar NVPs. In this example (Fig. 6), the EnOpt NVP is similar to multiscale regularized BOBYQA, but the estimated optimal controls for producers 1 and 5 are quite different. This can be further explained by **Fig. 7**, where

$$\sigma_m = \sqrt{\frac{\sum_{i=1}^{N_x}(x_{i,m} - x_{i,best})^2}{N_x - 1}}.$$

The deviation of g_m (m indicates different methods) from g_{best} can be calculated as $(g_{best} - g_m)$. The nonoptimized control variance σ_o and net value of production g_o are used for normalization. The loss in optimized g_m increases with the increase of deviation of X_m from X_{best}. However, the penalty in the value of production is small (less than 0.3%) for the optimized cases, even if there is a significant difference in control values (σ_m/σ_o =0.88). Such small differences in optimality for such markedly different control strategies (Figs. 4–5) are somewhat surprising.



(a) EnOpt

(b) Multiscale regularized EnOpt

(c) BOBYQA

(d) Multiscale regularized BOBYQA

Figure 4: Change of control variables with simulation runs: producer 1. Multiscale regularized methods give simpler control strategies. The coarse scale optimizes in some average sense, providing a good initial estimate for next finer scale.

Extensions. Only time scale regularization is considered in our synthetic case. For life cycle production optimization with many wells or well segments, regularization both in time and space might be more efficient (Lien et al. 2008).

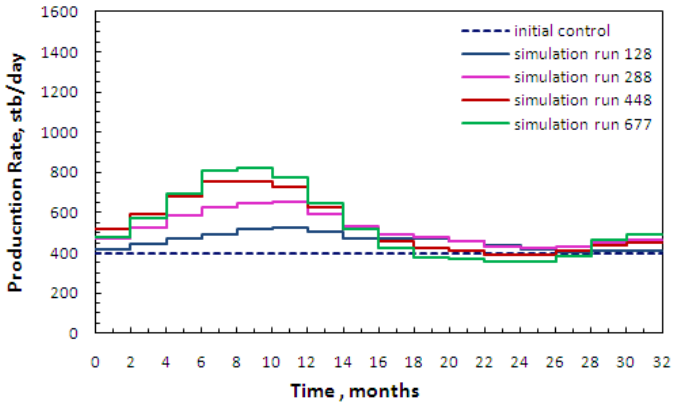
One disadvantage of ordinary multiscale regularization is that the refinement is carried out uniformly instead of adaptively, resulting in local over–parameterization and wasting simulation runs in methods like BOBYQA. Examing Fig. 4(b) as an example, for the last 16 months, only one control variable is needed whereas four control variables are assigned at scale 8. Adaptive multiscale regularization may be a good way to solve this problem. Methods for effective adaptive multiscale regularization with EnOpt and BOBYQA methods need to be further investigated.

Conclusions

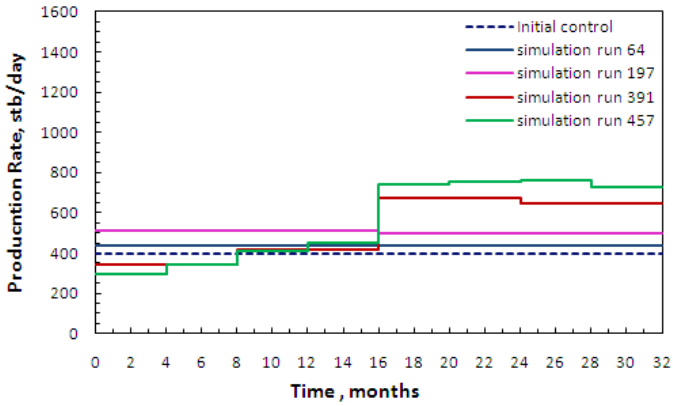
Two simulator–independent methods of smart well production optimization were investigated, EnOpt and BOBYQA. Multiscale regularization was tested on these two methods including examining effective control adjustment frequencies. The BOBYQA method is not as efficient as EnOpt method for optimization problems with more than a hundred unknowns because the BOBYQA method is prone to converging to local optima.

Multiscale regularization is promising for production optimization. The advantages of applying multiscale regularization on well control optimization include:

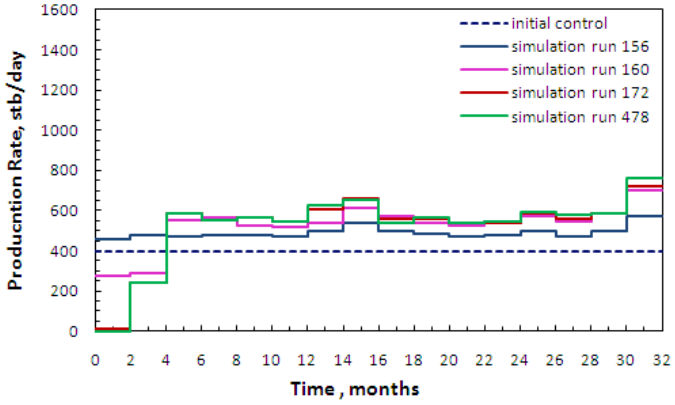
- Mutiscale regularized well control optimization is more efficient than direct fine-scale optimization.
- Regularizing the well controls makes the optimization problem for coarse scale less undetermined.
- The solution from the coarse scale appears to be less likely to converge to a local optimum.
- Coarse–scale early iterations provide a good starting point for the next finer scale, resulting in higher optima and better convergence speed.
- Instead of using a priori determined control adjustment frequency, mutiscale regularization finds the best control adjustment frequency by increasing control frequency successively until further refinement does not increase NVP.



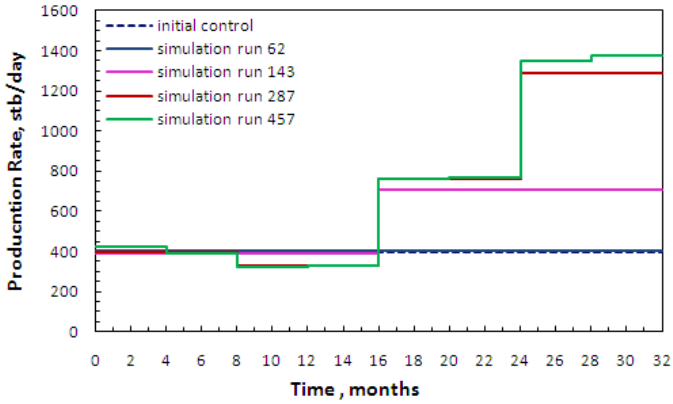
(a) EnOpt



(b) Multiscale regularized EnOpt

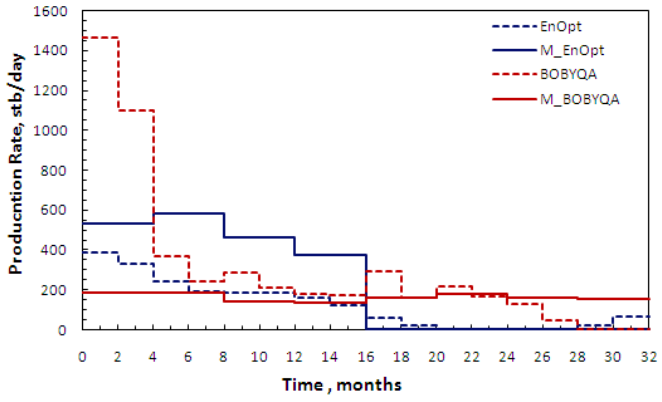


(c) BOBYQA

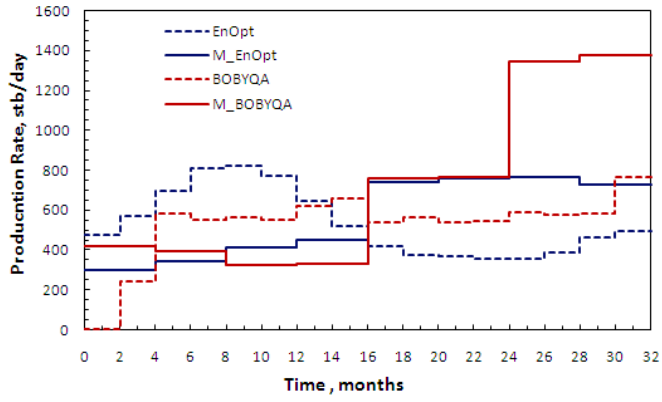


(d) Multiscale regularized BOBYQA

Figure 5: Change of control variables with simulation runs: producer 5. Multiscale regularized methods give simpler control strategies. The coarse scale optimizes in some average sense, providing a good initial estimate for next finer scale.



(a) Producer 1



(b) Producer 5

Figure 6: Comparison of optimized controls from EnOpt, multiscale regularized EnOpt, BOBYQA and multiscale regularized BOBYQA. Similar trends are obtained for different methods.

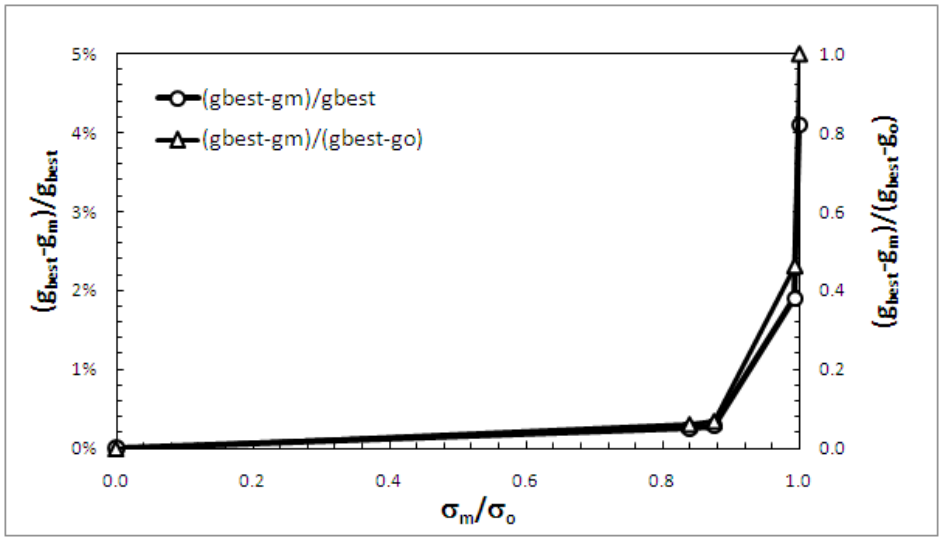


Figure 7: The deviation of optimized g_m from g_{best} increases with the deviation of well controls X_m from the best controls X_{best}. The penalty in the value of NVP is small (less than 0.3%), even when there is a significant difference in control values (σ_m/σ_o =0.88 with σ_o=275 stb/day)

Acknowledgements

We acknowledge Computer Modeling Group, Ltd. for donating licenses for reservoir simulators to Louisiana State University.

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