Journal of Petroleum Science and Engineering 119 (2014) 123–138

Contents lists available at ScienceDirect

Journal of Petroleum Science and Engineering

journal homepage: www.elsevier.com/locate/petrol

Biobjective optimization for general oil field development

Obiajulu J. Isebor*, Louis J. Durlofsky

Department of Energy Resources Engineering, Stanford University, Stanford, CA 94305, USA

ARTICLE INFO

Article history:
Received 6 October 2013
Accepted 29 April 2014
Available online 9 May 2014

Keywords:
biobjective optimization
derivative-free optimization
petroleum field development
mixed-integer nonlinear programming
multiobjective programming
optimization under uncertainty

ABSTRACT

The optimization of oil field development and production planning typically requires the consideration of multiple, possibly conflicting, objectives. For example, in a waterflooding project, we might seek to maximize oil recovery and minimize water injection. It is therefore important to devise and test optimization procedures that consider two or more objectives in the determination of optimal development and production plans. In this work we present an approach for field development optimization with two objectives. A single-objective product formulation, which systematically combines the two objectives in a sequence of single-objective optimization problems, is applied. The method, called BiPSOMADS, utilizes at its core our recently developed PSO–MADS (Particle Swarm Optimization–Mesh Adaptive Direct Search) hybrid optimization algorithm. This derivative-free procedure has been shown to be effective for the solution of generalized field development and well control problems that include categorical, discrete and continuous variables along with general (nonlinear) constraints. Four biobjective field development and well control examples are solved using BiPSOMADS. These examples include problems that consider the maximization of both net present value and cumulative oil production, and the maximization of both long-term and short-term reservoir performance. An example that highlights the applicability of biobjective optimization for field development under geological uncertainty is also presented. This usage of BiPSOMADS enables us to maximize expected reservoir performance while reducing the risk associated with the worst-case scenario.

1. Introduction

The goal in practical engineering problems is, commonly, to obtain designs and operating modes that represent an appropriate balance between multiple, possibly conflicting, objectives. The field of multiobjective optimization enables the solution of problems of this nature. In general there is no single solution that optimizes all objectives, but rather a set of optimal solutions that define a so-called Pareto front, which represents the optimal tradeoff between the different objectives (Rao, 2009). Our goal in this work is to develop and apply a computational framework for generating Pareto fronts in general oil field development and well control optimization problems.

General oil field development optimization entails the determination of the optimal number, type and locations of new wells, the sequence in which they should be drilled, and their time-varying controls. There have been many studies addressing different aspects of this general problem, though they typically considered just a single objective, such as net present value (NPV) or cumulative oil recovery. The well control optimization component of the problem involves the determination of optimal values for continuous operating variables, such as well rates or bottomhole pressures (BHPs). This problem has been addressed by many researchers, including Brouwer and Jansen (2004), Sarma et al. (2006), Doublet et al. (2009) and Su and Oliver (2010), who applied gradient-based procedures, and Almeida et al. (2007) and Echeverría Ciaurri et al. (2011), who considered derivative-free methods. The well placement portion of the general optimization problem entails the determination of the type and location of new wells. Recent studies focusing on well placement optimization include, e.g., Onwunalu and Durlofsky (2010) and Forouzanfar and Reynolds (2013).

The well placement and well control aspects of the general problem have traditionally been addressed sequentially, in a decoupled manner. Recent work, however, has demonstrated that the optimal locations for new wells depend on the manner in which they are controlled (Zandvliet et al., 2008; Bellout et al., 2012). Therefore, optimization strategies that do not consider the coupling between the two problems can yield suboptimal results. Studies that have applied joint (simultaneous) optimization of well placement and control include Bellout et al. (2012), Humphries et al. (2013), Isebor et al. (2013), Li and Jafarpour (2012) and Li et al. (2013).

* Corresponding author. Now at BP America Inc., Houston, TX 77079, USA.
E-mail addresses: obiajulu.isebor@bp.com (O.J. Isebor), lou@stanford.edu (L.J. Durlofsky).

http://dx.doi.org/10.1016/j.petrol.2014.04.021
0920-4105/

In recent work (Isebor, 2013; Isebor et al., 2014), we introduced and applied noninvasive derivative-free methods for the general oil field development optimization problem. Our formulation enables the simultaneous optimization of the number, type, drilling sequence, location and control schedules of new wells. Bound, linear and nonlinear constraints are all handled within the overall methodology. The general optimization problem contains categorical, integer and continuous variables, and thus represents a mixed-integer nonlinear programming (MINLP) problem. Our optimization framework entails a PSO–MADS hybrid algorithm that combines the local convergence properties of Mesh Adaptive Direct Search, MADS (Audet and Dennis, 2006) with the global search nature of Particle Swarm Optimization, PSO (Eberhart and Kennedy, 1995). Nonlinear constraints (an example of which is a maximum water production rate specification when the control variables are BHPs) are treated in both methods using filter methods, originally introduced by Fletcher et al. (2006). Our methodology has thus far been applied only for single-objective optimization problems. In this paper we extend this formulation to treat well control and field development optimization problems that involve two (generally conflicting) objectives.

There has been some previous work on the use of biobjective and multiobjective optimization within the petroleum engineering literature. Most of the applications of these approaches appear to be in the area of history matching, where various measures of misfit were minimized. Algorithms that have been applied for multicriteria history matching include multiobjective versions of Differential Evolution (as in Hajizadeh et al., 2011; Christie et al., 2013), PSO (as in Mohamed et al., 2011; Christie et al., 2013) and Genetic Algorithms (as in Ferraro and Verga, 2009; Sayyafzadeh et al., 2012).

Multiobjective optimization has also been applied for field development problems. Gross (2012) employed a decision analysis framework to determine the optimum number of wells and their corresponding plateau rates in order to maximize different objectives, such as recovery factor and duration of plateau production. Awotunde and Sibaweihi (2012) applied the weighted sum multiobjective approach to determine well locations with the goals of maximizing the NPV and the voidage replacement ratio. Yasari et al. (2013) considered a well control optimization problem involving three objectives. They used the Nondominated Sorting Genetic Algorithm (NSGA-II of Deb et al., 2002) to optimize the different components of NPV, with the goal of generating solutions that are robust with respect to geological uncertainty. The studies noted above applied multiobjective optimization only for specific components of the full field development problem, and none of them treated general (nonlinear) constraints, which commonly arise in practical settings. In our work here, by contrast, we address the general field development problem (i.e., we simultaneously optimize well location and type, time-varying controls, etc.), and we incorporate general constraints.

Our specific interest is in multiobjective optimization methods that generate an approximation to the full Pareto front. This provides the decision maker with a clear (and quantitative) picture of the optimal tradeoffs between the different objectives, and enables the selection of a compromise solution that appropriately balances the various objectives. Multiobjective optimization procedures of this type include weighted sum approaches (Das and Dennis, 1997; Kim and de Weck, 2006), where the weights of the objectives are varied such that multiple points on the Pareto front can be generated, population-based or evolutionary methods that attempt to sample the entire front using, e.g., GA (Deb et al., 2002) or PSO (Coello Coello and Lechuga, 2002), and the normal boundary intersection approach (Das and Dennis, 1998), which attempts to generate equally distributed points along the Pareto front using a sequence of optimizations. Recent approaches also include the use of direct search methods to solve a sequence of single-objective optimization problems, which generate progressively improved Pareto front approximations (Audet et al., 2008). Direct search methods that attempt to sample the entire front in a single optimization run have also been developed (Custódio et al., 2011).

In this paper we develop a biobjective optimization procedure, applicable for general field development problems, that entails the solution of a series of single-objective optimizations (Audet et al., 2008). We proceed in this way, rather than simply applying an existing multiobjective optimization code such as NSGA-II (Deb et al., 2002), in order to provide our biobjective optimization methodology with all of the advanced capabilities already incorporated in our PSO–MADS single-objective MINLP optimization algorithm. As noted above, these features include a global search capability combined with local convergence, treatments for different (mixed) variable types, and general constraint handling. As we will show, through solution of an appropriately formulated series of single-objective problems, our approach enables us to construct an approximation to the full Pareto front in realistic and challenging biobjective optimization problems.

This paper proceeds as follows. We first present the biobjective field development optimization problem statement followed by the biobjective optimization framework. A brief description of the underlying PSO–MADS hybrid method is then provided. Next, we illustrate our biobjective optimization procedure, called BiPSOMADS, which entails the solution of a series of single-objective PSO–MADS optimizations. Four example cases are then presented. These demonstrate the use of BiPSOMADS for optimizing NPV and cumulative oil recovery (with and without nonlinear constraints), and for maximizing long-term and short-term reservoir performance. We also apply BiPSOMADS to a problem involving geological uncertainty, in which we maximize both expected NPV and worst-case NPV. A summary and suggestions for future work are then provided. Appendix A presents a technical description of the BiPSOMADS optimization procedure.

2. Problem statement

The goal of optimization with multiple conflicting objectives is to generate the Pareto front, which is a representation of the optimal tradeoff between the different objectives. In multiobjective optimization, instead of considering a single objective f, we optimize the vector $\mathbf{f}$ as follows:

$$\min_{\mathbf{x}\in\Omega} \mathbf{f}(\mathbf{x}) = [f_1(\mathbf{x}), f_2(\mathbf{x}), \ldots, f_L(\mathbf{x})], \tag{1}$$

where L is the number of objectives and Ω represents the feasible region in optimization parameter space. Note that, for the general field development optimization problem, $\mathbf{x}$ in (1) consists of categorical variables $\mathbf{z}$, which define the number, type and drilling sequence of wells; discrete variables $\mathbf{v}$, which define the well locations on the simulation grid; and continuous variables $\mathbf{u}$, which define the time-varying well controls. In this work we focus on a formulation for optimizing just two objectives, i.e., we take $L=2$ and address the biobjective optimization problem, though much of our discussion is also relevant for multiobjective optimization with $L>2$.

In field development optimization, a common objective is the maximization of NPV (or a related economic measure), calculated using reservoir simulation. Thus we could have $f_1(\mathbf{x}) = -\mathrm{NPV}(\mathbf{u}, \mathbf{v}, \mathbf{z})$, with NPV given by

$$\mathrm{NPV}(\mathbf{u},\mathbf{v},\mathbf{z}) = \sum_{j\in I}\left[\frac{|z_j|C_j}{(1+b)^{t_j/\tau}} + \sum_{k=1}^{N_t}\frac{\Delta t_k c^{iw} q_{j,k}^{iw}(\mathbf{u},\mathbf{v})}{(1+b)^{t_k/\tau}}\right] - \sum_{j\in P}\left[-\frac{|z_j|C_j}{(1+b)^{t_j/\tau}} + \sum_{k=1}^{N_t}\frac{\Delta t_k (p^o q_{j,k}^o(\mathbf{u},\mathbf{v}) - c^{pw} q_{j,k}^{pw}(\mathbf{u},\mathbf{v}))}{(1+b)^{t_k/\tau}}\right], \tag{2}$$