Applied Soft Computing 34 (2015) 463–484

Contents lists available at ScienceDirect

Applied Soft Computing

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

Particle swarm algorithm with adaptive constraint handling and integrated surrogate model for the management of petroleum fields

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ARTICLE INFO

Article history:
Received 29 January 2014
Received in revised form 17 May 2015
Accepted 18 May 2015
Available online 28 May 2015

Keywords:
Adaptive constraint handling
Global search
Particle swarm
Reservoir simulation
Surrogate-based optimization
Waterflooding management

ABSTRACT

This paper deals with the development of effective techniques to automatically obtain the optimum management of petroleum fields aiming to increase the oil production during a given concession period of exploration. The optimization formulations of such a problem turn out to be highly multimodal, and may involve constraints. In this paper, we develop a robust particle swarm algorithm coupled with a novel adaptive constraint-handling technique to search for the global optimum of these formulations. However, this is a population-based method, which therefore requires a high number of evaluations of an objective function. Since the performance evaluation of a given management scheme requires a computationally expensive high-fidelity simulation, it is not practicable to use it directly to guide the search. In order to overcome this drawback, a Kriging surrogate model is used, which is trained offline via evaluations of a High-Fidelity simulator on a number of sample points. The optimizer then seeks the optimum of the surrogate model.

1. Introduction

The search for the optimum management scheme that maximizes oil production in petroleum fields is one of the major challenges in petroleum engineering. In this context, reservoir simulations and optimization methods are extensively used. Thus, Zhao et al. [1] use a *Simulated Annealing* based optimizer to determine the optimum steam injection pressure and steam-solvent flooding strategy in a thin heavy oil reservoir in the absence and presence of a bottom water zone.

Since the net present value (NPV) is related to the production profit, it is commonly used in reservoir engineering management as the objective function [1–4]. Waterflooding (WF) is the most widespread method used to improve oil recovery after primary depletion, i.e. after exhausting the reservoir's natural energy. The method consists of injecting water to raise the pressure and increase oil production. Horowitz et al. [2] propose four formulations of the WF management problem leading to optimization problems of different complexities, using the NPV as the function to be maximized subject to constraints at platform's total rates. They use a sequential approximate optimization (SAO) procedure with a sequential quadratic programming (SQP) local optimizer. This is a strategy proposed in [5], whose main feature is the sub-division of the original problem into a sequence of sub-problems to be solved in a sub-region of the original space named trust region (TR). Surrogate models to be called by the optimizer are built in the TR domain, which is updated as the search progresses [5–7]. This technique is also used by other researchers in the WF optimization context [3].

The concession period is usually subdivided into a number of control cycles with fixed switching times, with the well rates in each cycle set as design variables. Oliveira and Reynolds [4] 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 on 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.

While some of the formulations in [2] result in highly multimodal objective functions, the solutions found by the SQP optimizer are very sensitive to the initial guess. Hence we propose here to use a global search algorithm called particle swarm optimization

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http://dx.doi.org/10.1016/j.asoc.2015.05.032

(PSO). The latter is composed of particles with different settings aimed at displaying complementary capabilities, and a so-called forward topology with time-increasing connectivity for the social network. In addition, since the plain PSO algorithm does not handle constraints on its own, an adaptive constraint-handling technique (CHT) is developed and integrated into the optimizer. However, the fact that PSO is a population-based method also implies that it requires a high number of evaluations of the objective function. Given that the performance of a management scheme cannot be evaluated explicitly but by means of a computationally expensive high-fidelity (HF) simulation, it is not feasible to use it directly to guide the search. Surrogate-based optimization has proved useful to the optimization of computationally expensive simulation-based models in the aerospace, automotive and oil industries [8]. Therefore, it is proposed in this paper that a Kriging surrogate model (KM) [9,10] be used, which is trained offline via evaluations of a HF commercial simulator (IMEX [11]) on a number of sample points. The selection for this technique is based on results from previous work in which several procedures for the surrogate construction of the NPV function were tested [2,12].

The WF management problem is of high importance in petroleum engineering, whose objective is to increase productivity in petroleum fields using the rates of injector and producer wells as control parameters, thereby maximizing their economic return. In this paper, we show that a particle swarm (PS) algorithm with adaptive constraint handling and a static Kriging model can be combined to obtain near optimal results without the hassle of extensive numerical trial-and-error testing and tuning on a case-by-case basis. It is important to note that no tuning is carried out in this paper.

The layout of the paper is as follows: Section 2 presents the WF problem general formulation and four alternatives according to the operational conditions; Section 3 offers a discussion on surrogate models, in particular on Kriging approximations; Section 4 presents an overview of the PSO method, emphasizing the features that are used in our code; Section 5 presents the proposed PSO algorithm, including the formulation and settings of the particles' trajectory recurrence relation and neighborhood topology, and the development of a novel adaptive CHT and termination conditions; Section 6 presents the proposed integrated tool (PIT), consisting of the tandem Kriging-PSO for the global surrogate-based optimization of the WF problem; finally, results from computational experiments are offered in Section 7, a discussion of results is carried out in Section 8, whilst conclusions and future work are presented in Section 9.

2. Waterflooding problem formulation

The general formulation for the WF problem can be written as shown in Eq. (1):

$$\text{Maximize}\quad NPV = f(q) = \sum_{t=1}^{n_t}\left[\frac{1}{(1+d)^{\tau_t}}\cdot F(q_t)\right]$$

$$\text{Subject to}\quad \begin{cases} \sum_{p\in P} q_{p,t} \le Q_{l,\max} \\ \sum_{p\in I} q_{p,t} \le Q_{inj,\max} \\ q^l_{p,t} \le q_{p,t} \le q^u_{p,t};\quad p = 1,\ldots,n_w \\ \sum_{p\in P} q_{p,t} \le \sum_{p\in I} q_{p,t} \le \delta\cdot\sum_{p\in P} q_{p,t} \\ t = 1,\ldots,n_t \end{cases} \tag{1}$$

where $\mathbf{q} = \left[\mathbf{q}_1^T\mathbf{q}_2^T,\ldots,\mathbf{q}_{n_t}^T\right]^T$ is the vector of well rates for all control cycles; $\mathbf{q}_t = \left[q_{1,t},\ldots,q_{n_w,t}\right]^T$ 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 equation, d is the discount rate; τ_t is the time at the end of control cycle t; and $F(\mathbf{q}_t)$ is the cash flow at control cycle t, which represents the oil revenue minus the cost of water injection and water production. This is given by Eq. (2):

Table 1
Characteristics of the four formulations of the WF problem. Equality constraints are not transferred to the formulation of the optimization problems but reduce dimensionality instead.

Problem	Dimensionality (n)	Constraint type
FCO-FT	$(n_P+n_I-2)\cdot n_t$	Side, equality
NFCO-FT	$(n_P+n_I)\cdot n_t$	Side, inequality
FCO-VT	$(n_P+n_I-2)\cdot n_t+n_t-1$	Side, equality, inequality
NFCO-VT	$(n_P+n_I)\cdot n_t+n_t-1$	Side, inequality

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

where $\Delta\tau_t$ is the time length of control cycle t; P and I distinguish producer from injector wells; $q^o_{p,t}$ and $q^w_{p,t}$ are the average oil and water rates at production well p at control cycle t; r_o is the oil price; and c_w and c_{wi} are the costs of producing and injecting water. In Eq. (1), $Q_{l,\max}$ 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 refer to the lower and upper bounds of design variables, respectively. Superscripts o and w denote oil and water phases, respectively. The last constraint in Eq. (1) requires that, for all cycles, the total injection rate belong to an interval that goes from the total production rate to δ times this value, where $\delta \ge 1$ is the over injection parameter. The commonly used approach to these problems is to subdivide the concession period into a number of control cycles, n_t, with fixed switching times. The design variables are the well rates in each control cycle. Four alternative formulations derived from Eq. (1) are proposed in [2], where they combine different platform operational conditions with and without the inclusion of the switching times of the control cycles as design variables. The operational conditions considered are:

Full capacity operation (FCO), in which the sum of both production and injection rates are at maximum platform's total rates. Under this assumption, the last equation presented in Eq. (1) is automatically satisfied. These equality constraints actually simplify the problem, as they result in variables expressed in terms of others, thus reducing the dimensionality of the search-space and removing those constraints from the formulation of the optimization problem.

Non-full capacity operation (NFCO), in which the total injection and production rates may vary in order to increase the NPV, while the voidage replacement type constraints (last equation in Eq. (1)) are kept.

In this paper, situations where the control cycles are determined by the user are referred to as fixed time (FT) whereas those where the control cycles comprise design variables are referred to as variable time (VT). The cases resulting from the combination of operational conditions and types of switching times are depicted in Table 1. For each case, the number of design variables (n) and the type of constraints involved are shown. In the table, n_P is the number of producer wells and n_I is the number of injector wells. The mathematical formulation of each of these cases in Table 1 can be found in [2].

3. Surrogate models

Surrogate models are built to provide smooth functions accurate enough to capture the general trends of the HF model at a