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A comparative evaluation of global search algorithms in black box optimization of oil production: A case study on Brugge field

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ABSTRACT

We evaluate the application of eight different global search algorithms to the optimization of oil production from a mature field. Our focus is on algorithms that treat the reservoir simulator as a black box, which is the case for most commercial hydrocarbon reservoir simulators. The selected optimization algorithms have been divided in two categories. The first category consists of those algorithm that use approximated gradients, namely, simultaneous perturbation stochastic approximation (SPSA) and ensemble base optimization (En-Opt) methods. The second group includes derivative-free algorithms including particle swarm optimization (PSO), pattern search (PS), guided pattern search (GPS), covariance matrix adaptation evolutionary strategy (CMAES), differential evolution (DE) and self-adaptive differential evolution (SADE). GPS algorithm has been recently introduced and applied in oil production optimization by the authors (Foroud and Seifi, 2016) while the other algorithms have been developed and coded in MATLAB software according to the most renowned studies in the literature.

The selected algorithms have been applied to optimization of oil production in Brugge field. This problem is a bounded NPV optimization with 640 decision variables consist of injection and production rates over 10 years of operation and 200 linear inequality constraints. The results here show that algorithms that use approximated gradients (SPSA and En-Opt) and take advantage of physical properties of the underlying problem (GPS) are superior. Algorithms with self adaptation ability such as SADE and CMAES are the second best performers on this application. In fact, SADE which is the self adapted version of DE could achieve 7.5% more NPV than ordinary DE algorithm. Finally, in this study, GPS has been overall the most efficient algorithm with lowest number of function evaluations and the second highest NPV compared to other algorithms.

1. Introduction

Oil and gas resources have been provided the majority of required energy in last decades, and it is expected that they will retain their contribution to global energy for decades to come. On the other hand, many giant hydrocarbon fields around the world are mature with gradual production decline. Moreover, the number of new field discoveries is decreasing every year. As a result, a significant effort to optimize oil and gas production from existing resources seems to be crucial.

Hydrocarbon production optimization has been achieved an increasing attention during last decade due to its considerable costs and benefits. Production optimization in the field of reservoir engineering aims to find the optimal set of well controls in order to maximize or minimize an objective function such as net present value (NPV), accumulative oil or water production. The computation of the objective function requires predicting the reservoir dynamic behaviour under different decision variables (well controls). Since the relationship between the reservoir dynamics and the decision variables is in general nonlinear, finding the optimal set of well controls is a very challenging task. The objective function is usually computed using a numerical reservoir simulator which may contain several thousands to several hundreds of thousands grid blocks. Therefore, a commercial reservoir simulator is often required to predict the future performance of a reservoir which is computationally demanding for real reservoir models. As a result, hydrocarbon production optimization can be considered as a black box, simulation based optimization problem with expensive function evaluations.

This production optimization problem can be solved by applying various gradient based optimization methods. The required gradient of the objective function with respect to the controls can be computed using

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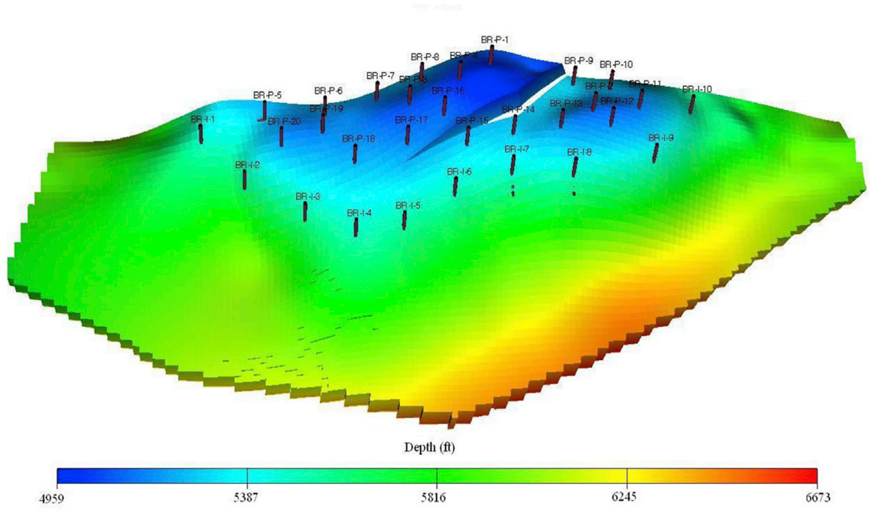

Fig. 1. Reservoir structure and well locations in Brugge field.

Table 1
The well Completions of Brugge field.

Well\Formation	Schelde Layers 1-2	Maas Layers 3-5	Waal Layers 6-8	Schie Layer 9
Injectors	Open	Open	Open	Open
Producers: 1–4, 6–8, 11–13 & 16–20	Open	Open	Open	Closed
Producers: 5, 10, 14 & 15	Open	Open	Closed	Closed
Producer 9	Open	Closed	Closed	Closed

Table 2
Economic parameters to calculate NPV for Brugge field.

Parameter	Value
Oil Price ($/bbl)	80
Water Operation Cost ($/bbl)	5
Water Injection Cost ($/bbl)	5
Discount Rate (percent per year)	10

numerical finite-differences (Aitokhuehi, 2004; Litvaket al, 2002; Wang et al., 2002; Yeten et al., 2002). This method demands a high number of function evaluations to obtain the gradient information. In addition, as it has been shown by (Asadollahi et al., 2014), the finite difference approximation of the gradients might be inappropriate and noisy. An efficient alternative is adjoint-based technique that greatly reduces the computational effort (Brouwer and Jansen, 2004; Jansenet al, 2009; Ramirez, 1987; Sarma, 2006; Sarma et al., 2008). However, adjoint-based techniques require full access to the simulator source code which is not possible in case of industrial reservoir simulators. Finally, it is important to note that gradient-based production optimization techniques, though computationally efficient, converge to local rather than global optima.

Application of derivative free optimization algorithms usually demands more function evaluations than gradient based methods. As a result, several researches have been done in order to reduce computational cost of such optimization problems using proxy models and reduce order modelling (ROM) (Cardoso et al., 2009; Cardoso, 2009; Chen, 2012). Authors have studied application of ROM in oil production optimization with and without considering uncertainty (Foroud and Seifi, 2016; Foroud et al., 2016). These studies have been done focusing on pattern search methods which have been led to introducing a guided search algorithm named Guided Pattern Search (GPS). GPS has been proved its applicability in oil production optimization of Brugge field in combination with ROM and geological uncertainties (Foroud et al., 2016). In this paper, we aim to compare the newly developed GPS algorithm with some distinguished optimization algorithms to more evaluate its efficiency in oil production optimization problem.

The aim of this study is to implement and assess several optimization algorithms, with emphasis on methods that do not require direct computation of gradient information. The algorithms studied herein can be classified in two different categories. First category includes methods like Ensemble base Optimization (En-Opt) and Simultaneous Perturbation Stochastic Approximation (SPSA) which use gradient approximations in their optimization process. The second division is derivative-free optimization algorithms that contain direct search methods (e.g. Pattern Search methods), a recently developed Guided search method (Guided

Table 3
Final Optimization outputs.

Order No.	Algorithm	Repetition	Opt. NPV	Function Evaluations	Initial point improvement (%)	Stopping Criterion
1	SPSA	3	3.659e+09	70002	27	Max. iteration
2	GPS	2	3.639e+09	11254	24	Mesh size
3	En-Opt	2	3.603e+09	22429	34	NPV Tolerance
4	CMAES	8	3.512e+09	28612	20	NPV Tolerance
5	SADE	2	3.403e+09	50100	35	Max. iteration
6	PS	4	3.190e+09	92774	9	Min. Mesh size
7	DE	2	3.165e+09	50100	26	Max iteration
8	PSO	6	3.128e+09	40000	12	Max. iteration