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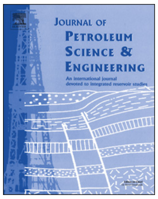

Production optimization using derivative free methods applied to Brugge field case

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ABSTRACT

Recently production optimization has achieved increasing attention in upstream petroleum industry. Here, we evaluate derivative free optimization methods for determination of the optimal production strategy using a numerical reservoir model which was prepared for a comparative study at the SPE Applied Technology Workshop in Brugge, June 2008. The pattern search Hooke–Jeeves, the reflection simplex Nelder–Mead, a new line-search derivative-free and a generalized pattern search methods are applied to the optimization problem. The line-search derivative-free algorithm is developed based on the existing line-search derivative free algorithms in combination with the Hooke–Jeeves pattern search method. The derivative free optimization results are compared with a gradient based sequential quadratic programming algorithm, but we clearly identify some issues limiting the performance of gradient based algorithms. In real applications our optimization problem is facing very costly function evaluations and at the same time one might have limitations in the computational budget. Therefore we are interested in methods that can improve the objective function with few function evaluations. The line-search derivative-free method performs more efficient and better than the other optimization methods. Ranking among the other four methods is somewhat more difficult, except that the Nelder–Mead method clearly has the slowest performance among these methods. We also observed that optimization with sequential quadratic programming had a high risk of getting trapped in a local optimum, which could be explained by properties of the objective function.

1. Introduction

Hydrocarbon reservoirs are the underground storages of oil/gas contained in porous rocks and geological formations. The hydrocarbon-bearing rock is referred to as the reservoir rock with two main properties: porosity and permeability. Porosity is the fraction of the rock that can be occupied by the fluids and permeability is the capability of the rock to transmit the fluids through the pore spaces. In general, after natural depletion (the first stage of oil production by natural reservoir drive mechanisms) a large portion of the hydrocarbon is trapped in the oil reservoirs, typically more than 60%. The trapped oil in the reservoir is subject to improved reservoir management. The reservoir management aims to increase the amount of hydrocarbon that is ultimately recovered from a reservoir. In line with this issue, production optimization (also known as reservoir optimization) has recently attracted increasing attention in the upstream petroleum industry while the downstream part of the industry is quite mature in this regard and advanced optimization algorithms are widely used in the petroleum refineries and petrochemical industry.

An oil reservoir generally contains gas, oil and water phases with oil as the dominant product. Gas, the lightest, occupies the upper part of the reservoir rocks; water, the lower part; and oil, the intermediate section. The oil reservoirs are developed with some wells to bring the oil to the surface. During the production phase, improved oil recovery (IOR) methods are designed to increase oil recovery. Waterflooding is a common IOR method in

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Abbreviations: BOBYQA, Bound Optimization BY Quadratic Approximation; BHP, bottomhole pressure; GA, genetic algorithm; GPS, generalized pattern search; HJ, Hooke–Jeeves; IOR, improved oil recovery; LSDF, line search derivative free; NM, Nelder–Mead; NPV, net present value; PSO, particle swarm optimization; QP, quadratic programming; SPE, Society of Petroleum Engineers; SPSA, Simultaneous Perturbation Stochastic Approximation; STB, Stock Tank Barrel; SQP, sequential quadratic programming; TNO, Dutch applied research organization; USD, United States Dollar; WCT, Water Cut

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which water is injected into a reservoir through the injection wells to remove the additional quantities of oil that have been left behind after natural depletion. The efficiency of a waterflooding project is affected by the swept volume of the reservoir from the injectors toward the producers. The geological heterogeneity (especially the permeability contrasts) of the reservoir layers as well as the density contrast (between the reservoir fluids, e.g. oil and water) can reduce the sweep efficiency of the project. In the last decade, the advances of downhole equipment, such as smart well completions, allow a better control on the sweep efficiency of a reservoir by production/injection rate allocation for different geological layers. Well completion is a term used to describe the assembly of downhole equipment required to enable safe and efficient production from an oil/gas well. A smart well completion refers to the installation of permanent downhole equipment for production/injection control and consists of some combination of zonal isolation devices, interval control devices and downhole control systems. Selective zonal control enables effective management of liquid production/water injection from/to the individual zones. A single production/injection well can be equipped with several smart completions (making it a smart well).

Traditionally, the general optimal settings of the production parameters were determined manually, see e.g. Czyzewski et al. (1992) and Ko et al. (1995). This requires a combination of tremendous technical efforts, judgment and experience and can result in suboptimal solutions. In some of the early reservoir optimization problems, Asheim (1988) and Virnovsky (1991) used mathematical optimization algorithms to maximize the net present value (NPV) or ultimate oil recovery for simple reservoir models. Asheim (1988) optimized the well rates to maximize the NPV from a two-phase (oil and water) reservoir under waterflooding. Virnovsky (1991) maximized the final oil recovery for a three-phase (oil, water and gas), two-dimensional model in homogeneous and heterogeneous porous media. He used the method of successive linearization to solve the optimization problem.

Advances in technology and increasing computational power provide the capability of the simulation of the large scale oil field models. This motivates the usage of advanced optimization techniques for reservoir optimization problems, see e.g. Brouwer and Jansen (2004), Sarma et al. (2008), Chen et al. (2010a). Recently, closed loop reservoir management has led to growing interest in optimizing the production strategy from a producing oil field using updated reservoir models. It consists of two main steps: model updating, also known as history matching or data assimilation to adjust the reservoir model parameters so that the model reproduces the historical behavior, such as production rates and pressures, of the real reservoir and production optimization to optimize the future production strategy from the reservoir (Jansen et al., 2005; Nævdal et al., 2006; Jansen et al., 2008; Wang et al., 2009). All the above papers suggest using gradient based methods, relying on an adjoint code for optimization. To develop the adjoint code one needs to have access to the reservoir simulator, and even if this is present it is still a cumbersome task to implement this. In many petroleum companies one uses commercial reservoir simulators ruling out the option of using adjoint solvers in the optimization. In such a case one might also face limited access to licenses of a reservoir simulator which restricts the potential of using distributed computation in the solution of optimization problems. Reservoir simulations are very time consuming for many real life problems. Therefore we are particularly interested in methods that improve the objective function with a limited set of function evaluations in the optimization process.

In a previous work (Asadollahi et al., 2012) we discussed how to reformulate a large scale optimization problem to a problem with an order of 50 optimization variables. Here we will compare different derivative-free optimization method for solving this problem.

We present an application of the derivative free methods to a reservoir optimization problem. Two pattern search methods, the **Hooke–Jeeves (HJ)** and the **generalized pattern search (GPS)**, a reflection simplex method, the **Nelder–Mead (NM)**, and a **line-search derivative-free (LSDF)** algorithm are tested and the results are compared with a derivative based method, **sequential quadratic programming (SQP)**. The HJ method is the recommended approach of Echeverría Ciaurri et al., 2011 when distributed computing resources are limited or not available at all. Although the NM is not well regarded by experts in optimization, it is still used by many practitioners; therefore we find it illustrative to include it in the comparison. The GPS is a modern method which is considered as an attractive choice due to the fact that a proper convergence analysis can be provided. We propose a new LSDF algorithm, which aims to improve the performance of the HJ by doing a better pattern search step by utilizing ideas from line-search methods described in Conn et al., 2009. Finally, we include a comparison with a gradient based method, SQP, but as will be pointed out later on, the directional derivatives might frequently be zero in this application.

The outline of the remaining part of the paper is as follows: firstly the optimization methods are described. Thereafter the optimization problem is clarified and formulated. We describe the initial guess used as a starting point for the optimization problem and discuss the step size used in the derivative free methods. We also discuss the selection of perturbation size for calculation of finite difference gradients used by SQP and at the same time illustrate why some of the directional derivatives become zero in many places. Finally the optimization methods are applied to solve the optimization problem and the results are illustrated and discussed.

2. Methods

Fluid flow through porous media is modeled using a mass conservation equation in combination with Darcy's equation. The final equations cannot be solved analytically and discretization techniques are needed to obtain a numerical reservoir model. The real numerical reservoir models can have several thousands to several hundreds of thousands of grid blocks. The physical rock and fluid properties are attributed to each grid block and the initial and boundary conditions are provided to the model (Aziz and Settari, 1979) to solve the flow equations numerically. In general, due to the diversity and large amount of work and data, different commercial software packages are used to build the final numerical reservoir model. Thereafter a commercial reservoir simulator is used to predict the future production from a reservoir. For real reservoir models, these simulations are computationally demanding. Therefore computation of the gradients of an objective function with respect to reservoir parameters comes with a prohibitive cost. Adjoint based optimization is used for solving large scale reservoir optimization problems. The major advantage of the adjoint method is obtaining the gradients in a single additional simulation, independent of the number of variables. However the implementation of the adjoint methods is not trivial and is a major programming effort. Moreover, its optimal implementation requires detailed knowledge of the reservoir simulator and access to the simulator code (Brouwer and Jansen, 2004; Sarma et al., 2008). Also automatic differentiation is typically impossible since the objective function is computed using a black-box model. In addition, as we show later in this paper, the finite difference approximation of the gradients might be inappropriate and noisy. Hence we use several derivative free methods