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Time-explicit methods for joint economical and geological risk mitigation in production optimization

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ABSTRACT

Real-life applications of production optimization face challenges of risks related to unpredictable fluctuations in oil prices and sparse geological data. Consequently, operating companies are reluctant to adopt model-based production optimization into their operations. Conventional production optimization methods focus on mitigation of geological risks related to the *long-term* net present value (NPV). A major drawback of such methods is that the time-dependent and exceedingly growing uncertainty of oil prices implies that long-term predictions become highly unreliable. Conventional methods therefore leave the oil production subject to substantial economical risk. To address this challenge, this paper introduces a novel set of *time-explicit (TE) methods*, which combine ideas of multi-objective optimization and ensemble-based risk mitigation into a computationally tractable joint effort of mitigating economical *and* geological risks. As opposed to conventional strategies that focus on a single long-term objective, TE methods seek to reduce risks and promote returns over the entire reservoir life by optimization of a given ensemble-based geological risk measure *over time*. By explicit involvement of time, economical risks are *implicitly* addressed by balancing short-term and long-term objectives throughout the reservoir life. Open-loop simulations of a two-phase synthetic reservoir demonstrate that TE methods may significantly improve short-term risk measures such as expected return, standard deviation and conditional value-at-risk compared to nominal, robust and mean-variance optimization. The gains in short-term objectives are obtained with none or only slight deterioration of long-term objectives.

1. Introduction

Despite a significant potential to improve key performance indicators (KPIs) central to oil reservoir management, real-life applications of model-based optimization remain challenged by a wide range of uncertainties related to e.g. unpredictable fluctuations in oil prices and sparse geological data. As opposed to geological uncertainties that are practically time-invariant, economical uncertainty grows exceedingly and profoundly with time. Conventional geological risk mitigation methods such as robust optimization (RO) (Van Essen et al., 2009) and mean-variance optimization (MVO) (Capolei, 2013) solely focus on risks associated with the *long-term* net present value (NPV) and they share the assumption of known economical model parameters. As a result, the profound time-dependent economical risks are altogether neglected and the long-term predictions become highly risky.

The literature has mainly accounted for economical uncertainty in terms of short-term versus long-term multi-objective optimization (MOO). The idea is to expedite short-term profits and thereby indirectly mitigate the risks that are imposed on the production strategy by time-dependent uncertainties. To accomplish this, Lui and Reynolds (2014) optimize a bi-criteria function for multiple different choices of a user-specified parameter to generate the Pareto front of short-term and long-term trade-off scenarios. Subsequently, each scenario is examined to determine the optimal solution. Such methods are referred to as *a posterior* methods and rely on multiple optimization runs to generate the Pareto front. This puts computational efficiency into question. Also, the optimizations often involve tuning of a user-specified set of weights, which may be non-trivial. Weight adjustments can be avoided by ϵ-constraint methods (Miettinen, 1999). Here a single objective is optimized subject to bound constraints on the other objectives. As a complication, the ϵ-constraint approach imposes non-linear constraints on the optimization problem and the question of how to choose the bounds arises. *A priori* hierarchical approaches, which only generate one solution, have been suggested by e.g. Van Essen et al., (2011),

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Fonseca et al., (2014b) and recently Siraj et al. (2015b). To ensure computational tractability, the methods rely on a heuristic switching scheme for which convergence properties are not fully understood at this point. Also, the convergence rate may be slow (Van Essen et al., 2011). As an alternative to the switching scheme, Chen et al. (2012) propose a hierarchical approach which relies on the augmented Lagrangian method. Recent studies investigate the effects on the balance between short-term and long-term objectives by considering an ensemble of n_e economical realizations (Siraj et al., 2015b, 2015c). The studies show promising results. However, it should be kept in mind that the uncertainties of oil prices are generally profound and grows exceedingly with time. Consequently, the dynamic nature of oil prices may become practically unpredictable and therefore highly difficult to model accurately over the long prediction horizons of open-loop production optimization. Typically, the reservoir life-cycle spans more than a decade. Also, as a tool for joint risk mitigation, each economical realization must be combined with each of the n_d geological realizations to calculate the gradients used for the optimization. In particular, $n_d \cdot n_e$ adjoint calculations are needed every time the optimizer calls the objective function. In practice, where large ensembles must be considered, the approach therefore becomes computationally intractable.

Combining the ideas of multi-objective optimization and conventional risk mitigation, this paper introduces a set of novel geological ensemble-based time-explicit (TE) optimization methods to address the issues of economical and geological uncertainties in a *united* manner. TE methods seek to balance short-term and long-term geological risk measures *over time*. In this way, time-induced economical uncertainties are *implicitly* addressed in the process. The proposed methods only rely on an ensemble of geological realizations. The computational effort is therefore much less involved as compared to approaches of combined model-based uncertainties. Further, it is shown that TE methods can be understood as *a priori* MOO methods with weights *predetermined* by discretization. As opposed to most MOO approaches of the literature, TE methods therefore avoid the expensive computations and cumbersome process of weight adjustments associated with generating the Pareto front. Open-loop simulations of a two-phase synthetic reservoir, where geological uncertainties are represented by an ensemble of 24 equiprobable permeability realizations, demonstrate that TE methods may provide significantly improved short-term risk measures including expected return, standard deviation and conditional value-at-risk, at *multiple points in time* as compared to conventional methods of geological risk mitigation. Long-term objectives are in turn only slightly compromised. The main contribution of this paper is the introduction and investigation of TE methods as alternatives to conventional ensemble-based methods. To better understand the risk mitigation effects of TE methods and their ability to balance short-term and long-term objectives, numerical experiments are conducted in an isolated open-loop setting. In this way, effects of data assimilation and feedback from a moving horizon principle will not interfere. Following Capolei et al. (2013), future studies are intended to clarify the risk mitigating effects of feedback by comparing open-loop and closed-loop TE strategies. Also, the paper focuses on mitigation of geological and economical risks. Other important factors of uncertainty such as future production infrastructure are not considered.

The paper is organized as follows. In Section 2 we briefly review fundamentals of water-flooding optimization. Conventional risk mitigation strategies are discussed in Section 3. Section 4 introduces the TE methods. Section 5 presents numerical results and conclusions are made in Section 6. Appendix A lists the nomenclature used in the paper.

2. Water-flooding

Water-flooding refers to the secondary stage of oil recovery in which water injection rates and producer bottom hole pressures are dynamically altered according to some operating profile, u, with the purpose of enhancing oil recovery. The work of this paper assumes that fluid flow through the reservoir may be approximated by a two-phase immiscible flow model based on mass conservation and Darcy's law. Relative permeabilities are described by the Corey model. Discretization in space and time with time-nodes $T = \{t_k\}_{k=0}^{N}$ results in the non-linear equations

$$R_k(x_{k+1}, x_k, u_k, \theta)=0, \quad k \in \mathcal{N} = \{0, 1\ldots, N-1\}, \quad x_0 = \hat{x}_0. \tag{1}$$

For each time-step, t_k, the state-space variables, $x_k = x(t_k) \in \mathbb{R}^{2n_x}$ denote reservoir pressures and fluid saturations, $u_k = u(t_k) \in \mathbb{R}^{n_u}$ the controls, and θ a set of petrophysical and geological model parameters. Here n_x and n_u denote the number of spatial nodes and the number of wells subject to control, respectively. See e.g. Aziz and Settari (1979), Chen (2007), Jansen et al., (2008) and Völcker et al., (2009).

3. Model-based optimization

Model-based optimization seeks to determine the operating profile that maximizes the life-cycle NPV, $\varphi(t_f)$, which is defined as the integral

$$\varphi(t_f) = \int_{t_0}^{t_f} \Phi(x(s), u(s))\, ds, \tag{2}$$

over the reservoir life, t_f, of the discounted profit, Φ, where

$$\Phi = \frac{-1}{\left(1 + \dfrac{d}{365}\right)^{\kappa(t)}} \left[\sum_{i \in P} (r_o q_{o,i}(t) - r_{wp} q_{w,i}(t)) + \sum_{l \in I} r_{wi} q_l \right]. \tag{3}$$

Here r_o, r_{wp} and r_{wi} denote respectively the oil price, the water separation cost, and the water injection cost; $q_{w,i}$ and $q_{o,i}$ are the volumetric water and oil flow rates at producer i; q_l is the volumetric well injection rate at injector l; the discount factor $-1/(1 + \frac{d}{365})^{\kappa(t)}$ accounts for the daily compounded value of the capital, where d is the annual interest rate and $\kappa(t)$ is the integer number of days at time t. Note that by convention, production rates are negative to indicate extraction. This accounts for the minus sign in the discount factor.

3.1. Problem formulation

The optimal control problem considered in this paper may be formulated as a constrained optimization problem in the form

$$\max_{\{x_k\}_{k=0}^{N}, \{u_k\}_{k=0}^{N-1}} \phi = \phi\left(\{x_k\}_{k=0}^{N}, \{u_k\}_{k=0}^{N-1}; \theta \right) \tag{4a}$$

$$\text{s. t. } R_k(x_{k+1}, x_k, u_k) = 0, \quad k \in \mathcal{N}, \tag{4b}$$

$$x_0 = \hat{x}_0, \tag{4c}$$

$$c\left(\{u_k\}_{k=0}^{N-1} \right) \le 0. \tag{4d}$$

The problem (4) seeks to determine the reservoir states, $\{x_k\}_{k=0}^{N}$,