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Offset Risk Minimization for Open-loop Optimal Control of Oil Reservoirs ⋆

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Abstract: Simulation studies of oil field water flooding have demonstrated a significant potential of optimal control technology to improve industrial practices. However, real-life applications are challenged by unknown geological factors that make reservoir models highly uncertain. To minimize the associated financial risks, the oil literature has used ensemble-based methods to manipulate the net present value (NPV) distribution by optimizing sample estimated risk measures. In general, such methods successfully reduce overall risk. However, as this paper demonstrates, ensemble-based control strategies may result in individual profit outcomes that perform worse than real-life dominating strategies. This poses significant financial risks to oil companies whose main concern is to avoid unacceptable low profits. To remedy this, this paper proposes *offset risk mimimization*. Unlike existing methodology, the offset method uses the NPV *offset* distribution to minimize risk *relative* to a competing reference strategy. Open-loop simulations of a 3D two-phase synthetic reservoir demonstrate the potential of offset risk minimization to significantly improve the worst case profit offset relative to real-life best practices. The results suggest that it may be more relevant to consider the NPV offset distribution than the NPV distribution when minimizing risk in production optimization.

Keywords: Optimal control, Model-based control, Production control, Risk, Stochastic modelling.

1. INTRODUCTION

Industrial strategies of oil field water flooding rely on reactive control to shut in producer wells as they become unprofitable. To enhance production, the oil literature has proposed optimal control technology, including nonlinear model predictive control (NMPC). The use of NMPC is referred to as closed-loop reservoir management (CLRM) (Jansen et al., 2009). The goal of CLRM is to determine the optimal operating profile that maximizes a key performance indicator (KPI) over the reservoir life-cycle, e.g, the cumulative oil recovery or a financial measure such as the net present value (NPV). CLRM consists of 1) an optimizer that uses the reservoir model to determine the optimal operating profile by solving a constrained open-loop optimization problem and 2) a state estimator for history matching to update the reservoir model as new data becomes available. This paper focuses on the optimizer, i.e. feedback and state-estimation is not considered. In the oil literature, this open-loop optimal control problem is referred to as life-cycle production optimization. The problem corresponds to computing the a priori optimal operating profile before the oil recovery process has begun and feedback becomes available. While simulation studies have demonstrated a significant potential of production optimization to increase overall profit, real-life applications are challenged by a wide range of uncertainties tied to reservoir simulation. To address the challenges of uncertainty, the oil literature has considered *ensemble-based* methods. Such methods represent the uncertainty by approximating the continuous NPV distribution by a finite number of possible outcomes, i.e., by an *ensemble of realizations*. To minimize risk, the ensemble members are combined to form a sample estimated risk measure that is optimized over the reservoir life-cycle. Popular ensemble-based methods include robust optimization (RO) (Van Essen et al. (2009)), mean-variance optimization (MVO) (Bailey et al. (2005), Capolei et al. (2015b)) and conditional value-at-risk optimization (CVaRO) (Capolei et al. (2015a), Siraj et al. (2015), Codas et al. (2016)). Such methods have proven to reduce overall risk relative to real-life dominating strategies of reactive control. However, ensemble-based control strategies may still result in individual profit outcomes that perform worse than reactive control. For reservoir asset managers whose primary concern is profit loss, this poses a significant risk of unacceptable low profit realizations. Therefore, despite overall lower risk, oil companies may be inclined to discard ensemble-based methodology. To meet this challenge, this paper proposes *offset risk minimization*. The offset approach seeks to determine the control strategy that minimizes the risk of performing worse than a competing reference strategy. To this end, the method maximizes the worst-case outcome of the *NPV offset distribution*. As opposed to methods of the oil literature, the offset approach mitigates the risk of low profit realizations *relative* to the

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competing reference strategy. In this way, the risk of profit loss relative to industrial standards is minimized. Using an ensemble of 100 realizations of a 3D synthetic reservoir, open-loop simulations demonstrate the potential of offset risk minimization to significantly increase the offset worst-case scenario relative to reactive control. Compared to the conventional use of the NPV distribution, the results suggest that the NPV offset distribution may be more relevant for risk mitigation in life-cycle production optimization.

The paper is organized as follows. In section 2, life-cycle production optimization under uncertainty is formulated as a risk minimization problem. Section 3 introduces offset risk minimization. Numerical results are presented in Section 4 and conclusions are made in Section 5.

2. LIFE-CYCLE PRODUCTION OPTIMIZATION UNDER UNCERTAINTY

Oil recovery by water flooding uses injection wells to dynamically inject water into the reservoir to displace hydrocarbons towards a set of production wells. The well injection strategy is referred to as the operating profile, u. The goal of life-cycle production optimization is to determine the operating profile that maximizes profit, ψ, over the reservoir life by solving the optimal control problem (Brouwer and Jansen, 2004; Sarma et al., 2005; Nævdal et al., 2006; Foss and Jensen, 2011; Völcker et al., 2011; Capolei et al., 2013):

$$\max_{u\in\mathcal{U}} \ \psi(u;\theta). \tag{1}$$

Here $\mathcal{U}$ expresses linear decision constraints and $\theta \subset \mathbb{R}^m$ represents geological, petrophysical and economical model parameters. In this paper, profit is given by the cumulative NPV, i.e.,

$$\begin{aligned}\psi(u,\theta) = \sum_{k=0}^{N-1} \frac{\Delta t_k}{(1+d)^{\frac{t_{k+1}}{\tau}}} \Bigg[& \overbrace{\sum_{j\in\mathcal{P}} r_o\, q_{o,j}\big(u_k, x_{k+1}(u,\theta)\big)}^{\text{value of produced oil}} \\ & - \overbrace{\sum_{j\in\mathcal{P}} r_{wP}\, q_{w,j}\big(u_k, x_{k+1}(u,\theta)\big)}^{\text{cost of separating produced water}} \\ & - \overbrace{\sum_{j\in\mathcal{I}} r_{wI}\, q_j\big(u_k, x_{k+1}(u,\theta)\big)}^{\text{cost of injecting water}} \Bigg].\end{aligned} \tag{2}$$

Here r_o , r_{wp} and r_{wi} denote the oil price, the water separation cost, and the water injection cost, respectively; $q_{w,i}$ 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; d is the discount factor, N is the number of control steps and $\Delta_{t_k} = t_{k+1} - t_k$ denotes the length of the time step. Well flow rates are computed using the Peaceman well model (Peaceman, 1983). For each time-step, t_k, the state-space variables, $x_k = x(t_k)$, denote reservoir pressures and fluid saturations whereas $u_k = u(t_k)$ represents a zero-order-hold parametrization of the well controls. The states x_k are computed by a two-phase immiscible flow model based on mass conservation and Darcy's law for porous media. Relative permeabilities are described by the Corey model. See e.g. Aziz and Settari (1979); Chen et al. (2006); Chen (2007); Völcker et al. (2009).

2.1 Risk mitigation by ensemble-based methods

The inaccessible geographical location of oil fields severely limits the amount of available geological data. Consequently, reservoir model parameters such as permeability, porosity and initial states are often highly uncertainty. The control strategy that solves (1) therefore imposes significant risks of profit loss and becomes unreliable for practical purposes. To reduce the financial risks of model discrepancies with real-life reservoirs, the oil literature has proposed ensemble-based production optimization. Ensemble-based methods represent geological uncertainty by a discrete set of equiprobable model realizations

$$\theta_{n_d} = \{\theta^1, \theta^2, ..., \theta^{n_d}\} = \{\theta^i\}_{i=1}^{n_d}. \tag{3}$$

The ensemble (3) is used to approximate the continuous NPV probability distribution by the related finite set of profit outcomes

$$\psi_{n_d} = \{\psi^i\}_{i=1}^{n_d}, \psi^i = \psi(u;\theta^i),\ 1 \le i \le n_d. \tag{4}$$

To minimize risk, the idea is to manipulate the discrete NPV profit distribution (4) by formulating an appropriate optimal control problem. To this end, it is customary to use a risk measure $\mathcal{R} : \psi_{n_d} \to \mathbb{R}$ to replace the overall profit distribution and quantify risk in terms of the scalar objective, $\mathcal{R}(\psi)$:

$$\min_{u\in\mathcal{U}} \ \mathcal{R}(\psi(u;\theta_{n_d})). \tag{5}$$

Figure 1 illustrates the key features of ensemble-based production optimization.

2.2 Specific risk measures and ensemble-based methods

Risk measures quantify the stochastic profit, ψ, by a numerical value, $\mathcal{R}(\psi)$, which serves as a surrogate for the overall profit distribution. The quantification of risk allows for fast and efficient decision-making. In particular, risk assessment of two scenarios, ψ' and ψ'', reduces to comparing the values $\mathcal{R}(\psi')$ and $\mathcal{R}(\psi'')$. However, the quality of the risk assessment heavily depends on the properties of the risk measure in question. The following briefly discusses the risk measures and related ensemble-based method used in this paper. Capolei et al. (2015a) provide a detailed overview of risk quantification in production optimization.

Robust optimization (RO) (Van Essen et al., 2009) refers to the ensemble-based method that maximizes the life-cycle sample estimated *expected return*, i.e.,

$$\mathcal{R}_{RO} := -\frac{1}{n_d}\sum_{i=1}^{n_d} \psi^i. \tag{6}$$

As a drawback, the expected profit is a risk neutral measure (Capolei et al., 2015a). As such, RO does not directly account for important risk indicators such as the lowest profit outcome.

Worst-case optimization (WCO) (Alhuthali et al., 2010) focuses solely on maximizing the lowest profit outcome, i.e.,

$$\mathcal{R}_{WCO} := -\min_{\theta^i} \psi(u;\theta^i) = -\tilde{\psi}. \tag{7}$$

Here $\tilde{\psi}$ denotes the lowest profit realization associated with the ensemble, i.e., $\tilde{\psi} \le \psi^i,\ 1 \le i \le n_d$. The restriction to a single profit outcome implies that the measure is blind