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Production Optimization under Uncertainty - Applied to Petroleum Production

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Abstract: A key challenge in production optimization is handling of model uncertainty. Traditionally, production optimization is done in a deterministic setting, ignoring the uncertainty. In this work, we formulate the problem as a two-stage stochastic programming problem. The solution to the problem is a strategy for operating the wells, instead of a single setpoint obtained from the deterministic problem. This strategy is easy to follow for the operator. A synthetic case study shows how the proposed approach increases the expected oil production by 1.5 percent.

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1. INTRODUCTION

In the exploitation of oil and gas, Real Time Optimization (RTO) can be used to optimize the production. RTO is a widely studied topic, see Tosukhowong et al. (2004), and although no widely accepted formal definition of RTO exists, it is used to denote a workflow where some of the decision variables are optimized by the use of mathematical optimization. A control hierarchy is often structured in layers according to time scales. In the context of upstream production, this hierarchy is divided into the four layers, asset management, long-term reservoir management, production optimization in daily operation, and control and automation (Foss and Jensen, 2011). We will in this work focus on production optimization, where typical control inputs include production choke opening and gas-lift rates. However, this layer is closely linked to the other layers, especially reservoir management. An early reference in the context of petroleum production is Saputelli et al. (2003), and a later overview of RTO can be found in Bieker et al. (2007a). The remainder of this paper will focus on this application domain.

In RTO, a mathematical model is employed when optimizing the performance of the system. This model is used to predict the outcome when changing decision variables, e.g. a model may describe an oil well by predicting flow rate for various choke openings. However, the model may fail to accurately predict the outcome due to model uncertainty. For example when the model is based on recent production data, it will often be accurate in the region around the current operating point, but poor when evaluated further away from this operating point. Models used in production optimization and reservoir management are inherently uncertain. This is due to the complexity of the system, difficulty in modeling multiphase flow and sparsity of well tests. If special precautions are not taken, the solution to the optimization problem might be in a region where we do not trust the model, and the output might thus have to be disregarded. The model uncertainty challenge was articulated in Bieker et al. (2007a); "The handling of model uncertainty is a key challenge for the success of RTO".

Although models are uncertain, this is often neglected when solving RTO problems. The most common approach is to solve what is known as the expected value problem. That is using the expected value of the uncertain parameters, e.g. using the gas-oil-ratio (GOR) and water cut (WC) from the most recent well test of each well. Thus, the fact that these values are uncertain does not enter into the formulation of the optimization problem. For an unconstrained problem, this might still be a viable approach, although no guarantee of optimality can be given. For a constrained problem, however, this approach has some serious flaws. Consider the production optimization problem where the objective is to maximize oil production, subject to a constraint on the gas processing capacity. When the gas processing capacity is limiting the production, the solution to the optimization problem will be at the constraint, that is, the modeled gas flow at the solution will be equal to the capacity constraint. If the solution were to be implemented directly, there is a chance that the constraint will be violated, but also a chance for the constraint to be inactive, such that there is spare capacity left. This happens because of model uncertainty, where the actual response of the system deviate from the model output.

The operator will, in a petroleum production setting, adjust the controls iteratively in order to reach the suggested setpoint. Thus, when there are multiple wells, there are multiple paths in order to reach the setpoint. If the operator discovers that he can not reach it, meaning it

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is infeasible, he might simply disregard it, and end up somewhere in between the prior operating condition and the suggested one. Thus, it is clear that the selected path will affect the outcome. However, this fact is actually not included in the optimization problem.

When solving the expected value problem, often denoted as the deterministic problem, we make the assumption that everything about the problem is perfectly known. We can then find a setpoint for all the control inputs, which will be optimal for the formulated problem. In this context, the solution will be feasible provided a feasible point exists. However, because of model uncertainty, there is a great chance the solution is unreachable. To overcome this, we can formulate the problem such that the solution will be feasible with a high probability. This can be done by using chance constraints, or in an even more conservative way, by applying a robust formulation. With chance constraints or a robust formulation, we can be quite certain that the solution will be feasible in practice, the drawback, however, is that the solution may be quite conservative.

In the deterministic world, where everything is known, it makes sense that the solution to the optimization problem is a setpoint for all the wells. In the real world, however, it is sensible to challenge this approach. *Thus, in this paper, we propose a two-stage optimization formulation that defines an operational strategy rather than a single operating point. We also argue that such a strategy fits nicely into the mindset of operators.*

We give a short overview of previous work in Section 2, before focusing on stochastic programming in Section 3. The mathematical formulation of our approach is given in Section 3.1. We then evaluate the approach on 3 different synthetic cases with increasing complexity in Section 4, ahead of a discussion of the results and conclusion in Section 5.

2. PREVIOUS WORK

There exists numerous publications on reservoir management under uncertainty, amongst others (van Essen et al., 2009; Chen et al., 2011). Uncertainty usually enters the reservoir optimization problems by the use of multiple realizations to span subsurface uncertainty. Published work does not, to the authors' knowledge, include capacity constraints, except for Chen et al. (2011), where they use a robust formulation to handle such constraints.

There are only a few published papers on short term production optimization under uncertainty. In Elgsæter et al. (2010), a structured approach for changing the setpoint when there is uncertainty is proposed. The uncertainty is, however, not considered in the optimization itself, only to assess the solution. To our knowledge, the only publication where the uncertainty is explicitly handled in the optimization problem is by Bieker et al. (2007b). They propose to formulate the optimization solution as a priority list between the wells. This list represents an operational strategy, thus whenever there is spare capacity or the opposite, the priority list is applied.

Although many deterministic formulations result in a single operating point, there are some methods which naturally extends to a strategy. The ideas of using incremental GOR for rate dependent wells in Urbanczyk and Wattenbarger (1994) and Barnes et al. (1990), can be thought of as strategies rather than providing specific operating points. However, these methods works for only one constraints, and are not easily extended for multiple constraints.

3. PRODUCTION OPTIMIZATION BY STOCHASTIC PROGRAMMING

A general deterministic optimization problem can be formulated as

$$\min_{x} J(x) \text{ s.t. } c(x) \leq 0 \tag{1}$$

When the problem contains uncertainty, both the objective and the constraints can be dependent on a stochastic parameters, denoted ω. Thus, the objective and constraints are no longer deterministic, but rather stochastic variables. To compare two different stochastic objective functions, we must compare distributions instead of scalars. A natural approach is therefore to compare expected values. Methods emphasizing some quantile of the distribution is also typical. Since the short term production optimization problem is solved on a daily basis over many years, it is reasonable to use the expected value. For the reservoir optimization problem, however, a more conservative approach could be more reasonable.

While handling uncertainty in the objective boils down to assessing distributions instead of scalars, constraints are fundamentally different. The satisfaction of a constraint on average is often inadequate, while a robust formulation ensuring that the constraints hold with probability 1, can lead to an overly conservative solution. A middle of the road approach is to use chance constraints, formulating the problem as

$$\min_{x} \mathbb{E}[J(x,\omega)] \text{ s.t. } \Pr.\{c(x,\omega) \leq 0\} \geq \alpha \tag{2}$$

so that the solution must hold with a predefined probability α. The solution of (2) will, however, with probability α have a margin to the constraint. In the production optimization problem with capacity constraints, this means there will probably be spare capacity when the solution is implemented. The operator might try to utilize this, but it is not included in the optimization problem. Thus, the final implemented operating point is dependent on the optimized solution and the operators implementation strategy.

Since the constraints are uncertain, it is not possible to provide the operator with a single setpoint for all the wells, such that it is feasible with probability 1, while at least one capacity constraint is active. However, we could specify a setpoint for each well, and in addition specify which well to turn up to utilize additional spare capacity. The initial setpoint should be feasible with a high probability. This is similar to how many fields are operated today, using a swing producer to utilize any spare capacity. The difference is that we include this information into the optimization problem itself, and the setpoint is calculated with awareness of this second phase. Which well to use as a swing producer will also be part of the solution to the optimization problem. Because of different well properties and dynamics, certain wells might be more suitable to

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