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Model-based Workflows for Optimal Long-term Reservoir Mangement

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SUMMARY

Life-cycle optimization is the process of finding field operation strategies that aim to optimize recovery or economic value with a long-term (years to decades) horizon. A reservoir simulation model is therefore generally appropriate and sufficient to explore the impact of different recovery scenarios. A number of challenges arise when trying to determining the optimal recovery strategy. We describe a practically feasible model-based optimization workflow that addresses complications associated with computational effort, large numbers of decision variables (controls), and the uncertainty in the properties of the reservoir. A software tool has been developed, in cooperation with industry partners, and applied to several synthetic and real field cases to demonstrate the value and potential benefits of this workflow, such as optimal well operating strategies for multiple wells that increase recovery or economic value, improved well design, and reservoir understanding.

Introduction

Life-cycle optimization is the process of finding well operation strategies that aim to optimize recovery or economic value with a long-term (years to decades) horizon. The dominant factors on such time scales are the reservoir rock and fluid properties, and the field development (number, placement and design of wells and completions) and recovery strategy (e.g. injected fluids). Day-to-day operational constraints can normally be assumed constant. A reservoir simulation model is therefore generally appropriate and sufficient to explore the impact of different recovery scenarios.
A number of challenges arise when trying to determine the *optimal* recovery strategy: 1) A single model simulation may take a long time; 2) The number of decision variables (*controls*) is generally very large (hundreds to tens of thousands), which makes it practically infeasible to test all possible combinations of values; 3) The properties of the reservoir are always unknown to some extent, and the reliability of results obtained with a single model is therefore very limited; 4) Some strategies that result as combinations of specific control values may be infeasible in reality and appear as rather complex constraints on allowable outcomes of the optimization; 5) Strategies based only on reservoir model simulations may not be acceptable as hard targets for day-to-day operations due to the neglect of factors that affect actual production behaviour (well work-overs, failure or shut-ins, near-well heterogeneity, etc.) or due to the requirement for frequent intervention by the well operator, which is generally undesired as it increases risk of failure and operational costs. While approaches exist to address all these complications, we will focus here on describing a practically feasible approach to life-cycle optimization under uncertainty (points 1 to 3), and demonstrate its value in both an intuitive synthetic setting, as well as on a real field case.

Method

TNO, in cooperation with research partners, has developed a tool for ensemble-based reservoir life-cycle optimization. It is based on the widely supported notion that gradient-based optimization is the most efficient approach for solving optimization problems with very many controls, as is typical in life-cycle optimization. A practical method to obtain approximate gradients has been developed over recent years that enables use of gradients, also in cases where exact gradient information is not available (as is the case with all commercial simulators). The method, known as Ensemble Optimization (EnOpt), estimates approximate gradients from a limited number of simulations with randomly perturbed controls after which normal line search or trust region optimization strategies can be applied [1,2]. The current implementation effectively estimates gradients for up to 1000 controls by running only 50 or so simulations. Most importantly, it can deal efficiently with similar numbers of model realizations, representing uncertain geology or fluid properties, and obtain so-called *robust* strategies that are optimal in a probabilistic sense (e.g. in terms of the *expected* NPV or recovery). This also has the advantage that it connects well with history matching approaches that aim to deliver multiple models that all match the historic data, such as the Ensemble Kalman Filter.

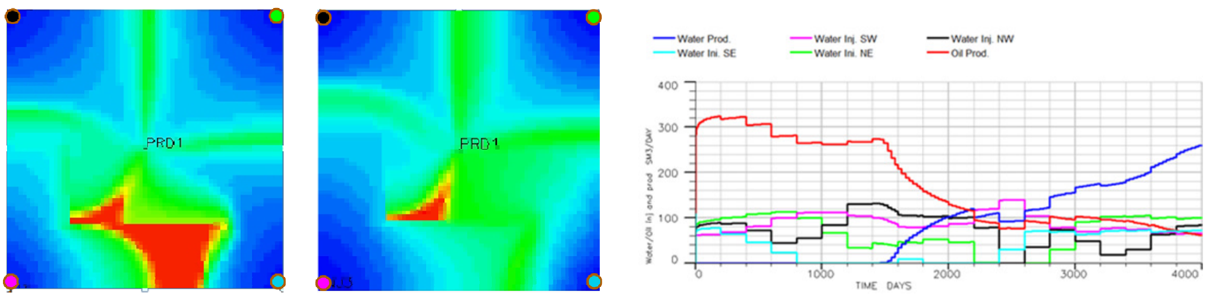

Figure 1 *Left: Remaining oil saturation resulting from a standard operating strategy. Middle: Remaining oil resulting from an optimized strategy. Well colours correspond to the lines in the right panel. Right: Well rates in the optimal strategy.*

Example 1

The first example (Fig. 1) illustrates the principle of life-cycle optimization on a simple case with four injection wells and a single producer in a synthetic 2D oil reservoir containing a sealing L-shaped fault. A common production strategy, in which all injectors inject with equal and constant rates, is seen to leave a significant amount of oil behind. Model-based optimization of NPV, however, delivers a strategy that is able to sweep an additional amount of oil from behind the fault, thereby increasing NPV by 5%. The economic value results not only from a higher oil ultimate recovery, but also from a significant reduction in amount of injected and produced water, which could lead to further reductions in required facility capacities and therefore cost.

Example 2

The second example is a real field application in which two sectors from the same large field were considered with multiple injectors and producers each (Fig. 2). Optimal strategies were obtained for both the current development based on conventional wells, as well as a smart well scenario, in which each well is equipped with 3 inflow control devices (ICV) which can be opened or closed.

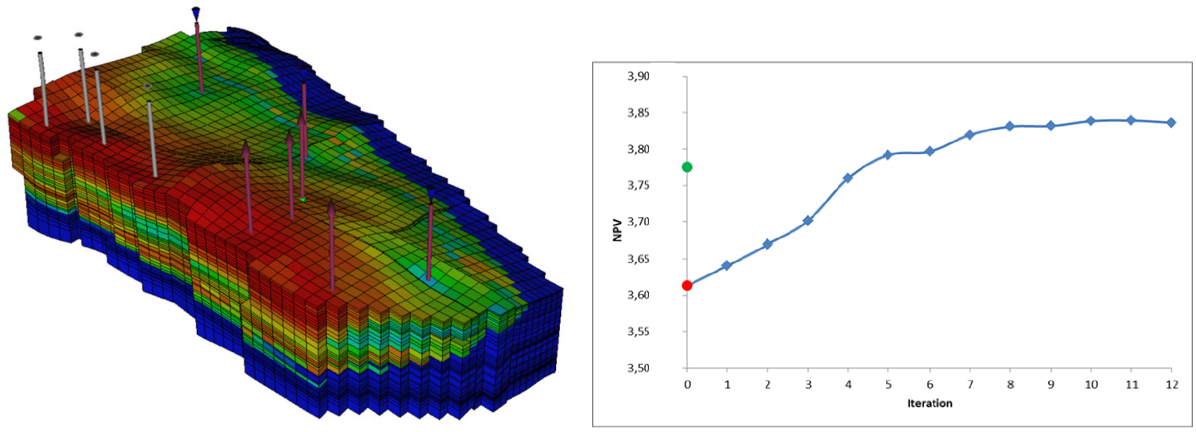

Figure 2 *Left: Sector model and well lay-out. Right: NPV resulting from optimal conventional well control (green dot), from some initial ICV strategy (red dot), and from optimized ICV control (blue line and dots) over a number of iterations during the optimization process.*

NPV for the smart well case is higher than for the conventional well case, mostly due to a significant reduction in water injection and production. The strategies resulting from both conventional and smart well development options were examined (not shown). It could be seen that the ICV operation within some wells was almost identical to the conventional well operating strategy, suggesting that there is no technical value in investing in instalment of ICVs, which can lead to substantial reductions in investment costs. Optimization results may also provide improved reservoir insight, indicating for example the sensitivity of dynamical behaviour to reservoir heterogeneity and uncertainty therein.

Conclusions

This work discusses the potential of advanced model-based reservoir optimization approaches in typical field cases with large complexity. Application of such a tool to an actual field case demonstrates the value for improved economics, field development and recovery. Although not shown here, the applicability can be extended to cases with uncertainty as well.

References

Chen, Y., Oliver, D.S and Zhang, D. [2009] Efficient ensemble-based closed-loop production optimization, *SPE Journal*, SPE 112873, 10.2118/112873-PA.

Leeuwenburgh, O., Egberts, P. and Abbink, A. [2010] Ensemble methods for reservoir life-cycle optimization and well placement. *SPE/DGS Annual Technical Symposium and Exhibition*, Al-Khobar, 4-7 April, SPE 136916.