PTE574 Final Project Report (Spring 2021)

Well control optimization of an oilfield operated under waterflood

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Abstract

Significant fraction of oil is left in reservoirs when utilizing only primary recovery methods. This necessicates the application of the secondary recovery methods such as water or gas injection. However, even after application of secondary recovery methods, still a large volume of oil remains in the subsurface reservoirs, leaving a room for application of novel methods to increase the recovery. Among many possible solutions, well control optimization is relatively cheap, widely applicable option to use for further optimization of the recovery. In this paper, well control optimization was applied one layer of SPE 10 model. Numerical model was simulated for 10 years and optimization frequency for controls was set to be once per year. Optimization was performed using interior point algorithm with bound constraints on well controls coupled with MRST reservoir simulator and adjoint formulation for gradient calculation. Using NPV as a performance measure, an increase of 9.4% was observed after application of optimization compared to a constant control strategy.

Introduction

Up to 15% of oil is recovered during primary recovery (Enhanced Oil Recovery, 2021), meaning that only a very small proportion of oil can be extracted by solely utilizing the natural energy of the reservoir. In most cases, primary recovery is accompanied by secondary recovery methods. Water and gas injection, which are two main methods for secondary recovery are used to supply an additional energy to the reservoir with the aim to increase the recovery. Secondary recovery methods result in differing levels of success and often the rate of recovery after application of these techniques is in the range of 10-50% (Jansen et al., 2008).

This potentially leads to the conclusion that more than half of the original oil in place cannot be recovered after application of secondary recovery techniques. Historically, enhanced oil recovery methods, also called as tertiary recovery methods, were the most popular approach to use for accessing the remaining volume of hydrocarbons that could not be recovered after application of secondary recovery techniques. During enhanced oil recovery, techniques or materials other than natural gas or water are utilized to displace the trapped oil. There is a wealth of techniques that are categorized as enhanced oil recovery methods such as miscible, thermal, microbial and chemical flooding (Uzoho et al., 2015). However, there are range of issues with the application of enhanced oil recovery methods. Generally, these methods are complex to design, develop and operate, as well as application of EOR techniques involves the use of large quantities of costly chemicals (Muggeridge et al., 2006), consequently disabling their applicability during the periods of relatively low oil prices. One of the alternative methods to increase the recovery factor is the use of computational optimization procedures (Jansen and Durlofsky, 2016). These

optimization procedures can be used to address a range of reservoir management decisions such as determination of optimal number, type, location, operational controls of wells and their drilling schedules. In this paper, we discuss the application of optimization techniques to well control problem. The application of optimization algorithms to well operational controls is relatively new research area and have been inspired by model-based control techniques used in the process industry (Jansen et al., 2008). This area of research was enabled after the introduction of sensors and remotely controllable valves in wells and further accelerated after the availability of high-dimensional accurate reservoir models and development of fast computing techniques.
In this paper, well control optimization technique was applied to one layer of SPE 10 model. Resulting improvement in performance measure is compared to a case with constant controls. Additionally, oil saturation distributions and control trajectories for both optimized and constant control cases were illustrated and compared.

The well control optimization problem

In this section, the well control optimization problem, objective function of interest, control variables and constraints are introduced.
A range of objective functions can be formulated for well control problem depending on the optimization objectives, such as net present value, total oil produced, sweep efficiency etc. In this work, the net present value (NPV) is used as an objective function:

$$NPV(u) = \sum_{k=1}^{T} \left[\sum_{i=1}^{N_p} r_o * q_{o,i}(t,u) - \sum_{i=1}^{N_{inj}} r_{wi} * q_{wi,i}(t,u) - \sum_{i=1}^{Np} r_{wp} * q_{wp,i}(t,u) \right] * \frac{1}{(1+d)^{tk}} \Delta t \quad (1)$$

where,
u (vector**)** is the set of control variables during the reservoir's lifetime
$q_{o,i}$, $q_{wi,i}$, $q_{wp,i}$ respectively denote produced oil at producer i, injected water at injector i and producer water at producer i at kth timestep
r_o, r_{wi}, r_{wp} respectively denote oil price, water injection and produced water disposal costs
T is the total number of timesteps
N_p is the number of producers
N_{inj} is the number of injectors
d is the discount factor
Δt is timestep size
tk is time at the end of kth timestep.

In well control problem the decision variables which represent bottomhole pressures for producers and injection rates for injector wells, are encoded in **u** which is N_u dimensional column vector, representing total number of well controls. Once objective function and decision variables are defined, well control optimization problem with bound constraints can be formulated as follows:

$$\max \quad NPV(u) \tag{2}$$
$$subject\ to \quad u_{lb} \le u \le u_{ub} \tag{3}$$

where,
$NPV(u)$ is the objective function defined in equation 1
u_{lb} and u_{ub} are lower and upper bound constraints which define respectively minimum and maximum allowable values for control variables.

Case study

In this section, the description of the reservoir model used and optimization details are provided.

Reservoir model description

Reservoir model used in this project is based on one layer of the SPE10 model. Model represents two phase (oil and water), incompressible system operated under waterflooding regime and discretized into 60x220 gridblocks. There are 4 producer and 2 injector wells. Producers are operated under bottom hole pressure control, whereas injectors are controlled via total injection rate. The reservoir is simulated over 10 years using Matlab Reservoir Simulation Toolbox (MRST). The porosity and permeability distribution for the field is shown in Fig. 1 and Fig. 2 respectively. Summary of reservoir model properties is provided in Table 1.

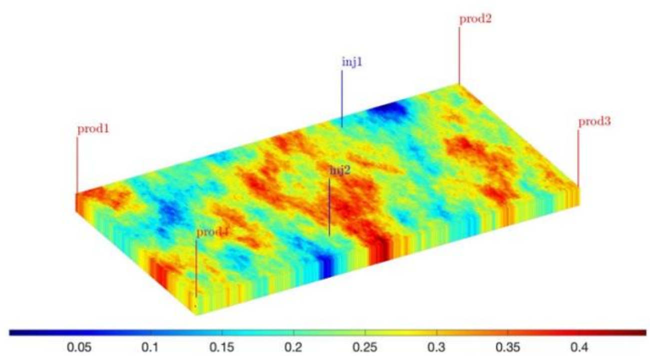

Figure 1. Porosity distribution for the field

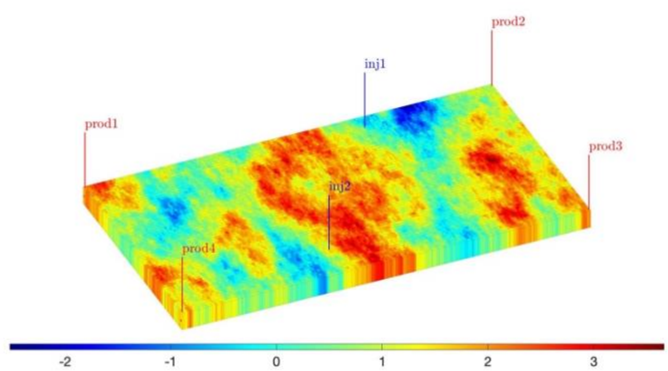

Figure 2. Permeability (kx=ky) distribution for the field

Number of the grid cells	60×220×1
Grid cell dimensions	20 ft× 10 ft× 50 ft
Fluid phases	Oil-Water
Simulated reservoir life cycle	10 years
Injectors control mode	Total water injection rate
Producers control mode	Bottomhole Pressure

Table 1. Summary of reservoir model

Optimization details

As mentioned in earlier sections, net present value (NPV) is used as an objective function in this project. The decision variables are bottom hole pressures for producers and injection rates for water injectors. Reservoir simulation duration was set to 10 years with control frequency being once per year for each well. In this setting, we have 10 control variables per each well, and as there are 4 producers and 2 injectors, 60 control variables in total. Bound constraints were applied to both producers (500-4500 psia) and injectors (100-700 $\frac{stb}{day}$). Therefore, the optimization can be formulated as nonlinear constrained optimization problem with bound constraints. Among available options in Matlab, interior point method is the recommended algorithm for large scale, sparse problems. (Choosing the Algorithm- MATLAB & Simulink, 2021). Gradient of objective function (NPV) with respect to control variables are calculated using adjoint method (Zandvliet et al., 2008). Summary of optimization details is provided in Table 2.

Objective function	NPV
Injector control	Injection rate
Producer control	Bottomhole pressure
Control frequency	Once per year
Reservoir simulation duration	10 years
Number of control variables	60
Gradient calculation method	Adjoint
Stop criteria	50 iterations

Table 2. Summary of optimization parameters

Results and Discussion

In this section we compare the results between the case with constant well controls and optimized well controls in terms of 1) NPV, 2) oil saturation distribution and 3) well control trajectories. Fig. 3 and table 3 show the plot of NPV vs number of iterations and comparison of base case NPV vs optized case NPV respectively. It is evident from the figure and table that after 50 iterations, optimization algorithm finds a control setting that leads to 9.4% relative increase in NPV with respect base case with constant controls.

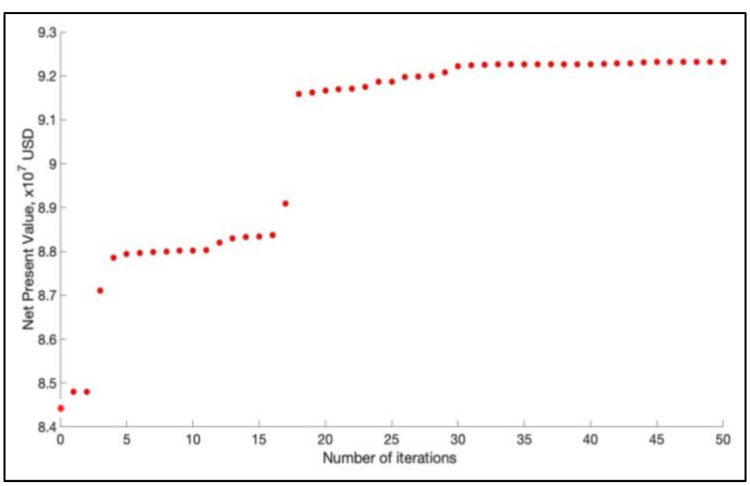

Figure 3. NPV vs number of iterations

NPV (base case)	NPV (optimized)
8.44×10^7 USD	$9.23 \times 10^7\ USD$
7.9 million USD of incremental NPV	
9.4% relative increase in NPV achieved	

Table 3. NPV (base case) vs NPV (optimized)

Fig 4. and Fig. 5 respectively illustrate base case and optimized case control trajectories. It is suggested in the literature that if only constraints are upper and lower bounds, optimization problem can have bang-bang optimal solutions (Zadvliet et al., 2007). Bang-bang control refers to a control case when controller, in our case bottom hole pressure control or water injector control valves, switches abruptly between two extreme cases. Having bang-bang controls has practical advantage since these controls can be implemented with on-off valves (Zadvliet et al., 2007). However, in our example, we do not observe bang-bang control solution, that is all transitions between controls are gradual. This is due combination of the facts that 1) optimization algorithm was stopped after 50 iterations, meaning the solution is not optimal one and 2) as stated in the literature, bang-bang controls are not strictly observed as solution in all well control optimization problems.

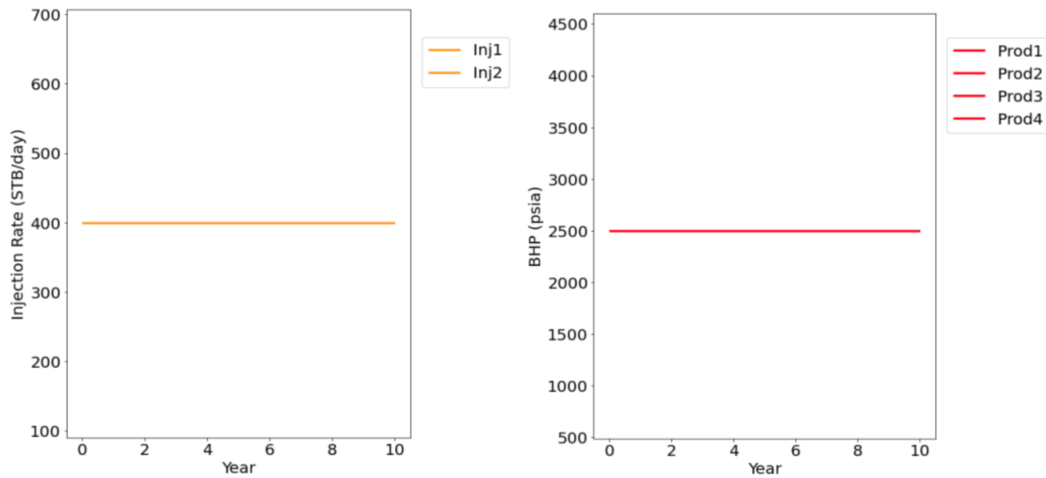

Figure 4. Base case control trajectory

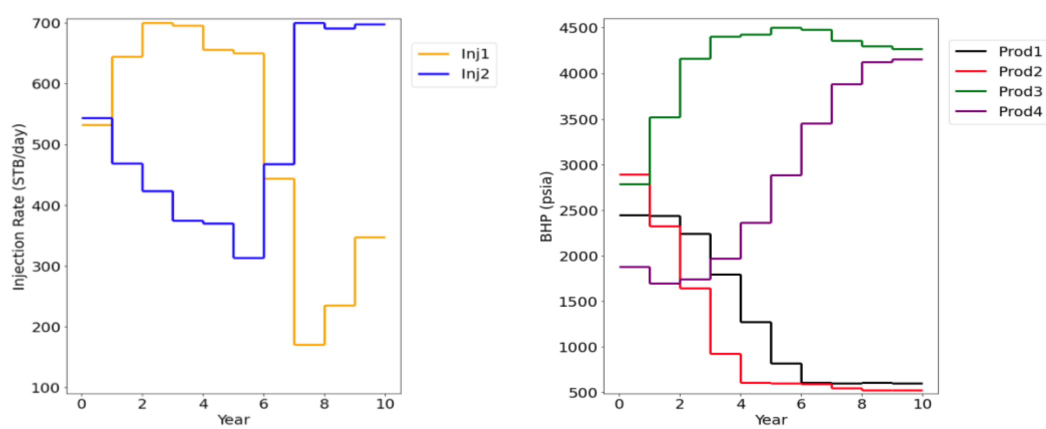

Figure 5. Optimized control trajectory

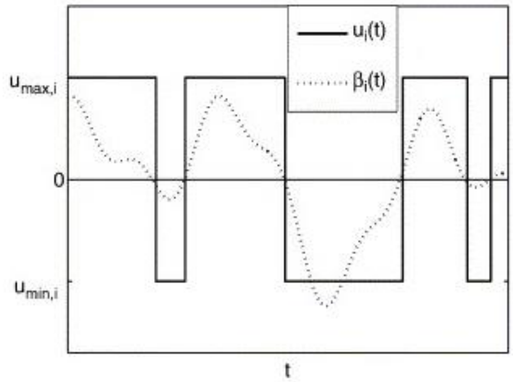

Figure 6. Bang-bang control $u(t)$ (Zadvliet et al., 2007)

Fig.7 and Fig. 8 illustrate the oil saturation distribution for the base case with constant controls vs oil saturation distribution for the case with optimized controls respectively. Overall, no significant change in fluid flow paths is observed, optimized controls, overall, accelerate the recovery and thus, at the end of 10-year period, lower oil saturation is observed across the model.

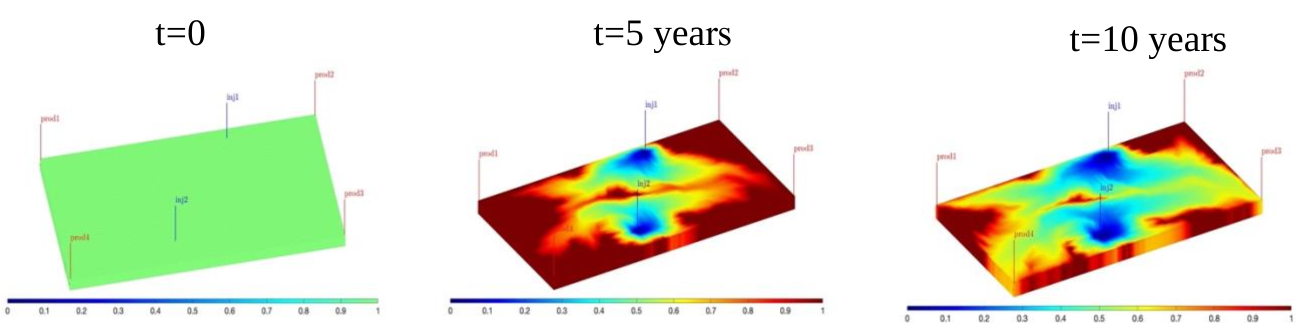

Figure 7. Oi saturationl distribution base case

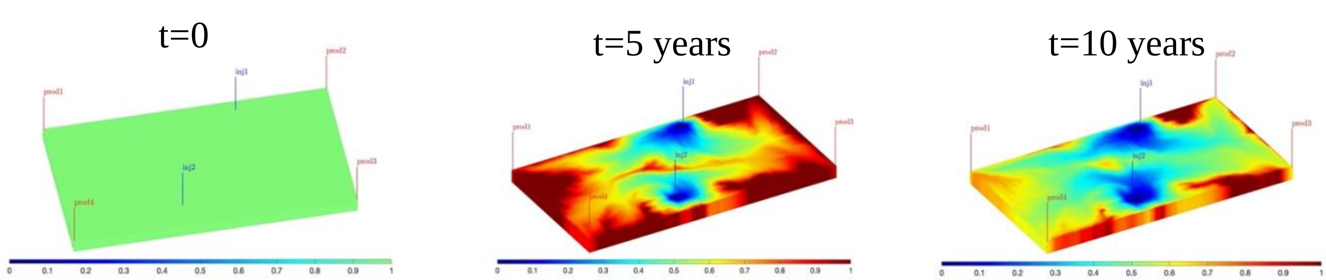

Figure 8. Oil saturation distribution optimized case

Conclusions

In this paper, well control optimization has been presented as an alternative option for further increase of the recovery in reservoirs operated under waterflood. Well control optimization workflow was applied to one layer of SPE 10 model. With the reservoir simulation duration set to 10 years and well control frequency of once per year, having in total 4 production and 2 injector wells, led to 60 decision variables. Imposing bound constraints on decision variables and nonlinear nature of objective function enabled formulation of problem as nonlinear constraint optimization problem with bound constraints. The results suggest that with NPV as performance measure, optimized set of controls generated an incremental NPV of 7.9 million USD, compared to a base case with constant controls. Additionally, well control trajectories and oil saturation distributions between the base case scenario and a case with optimized well controls were compared and differences were discussed.

References

1. Energy.gov. 2021. Enhanced Oil Recovery. [online] Available at: <https://www.energy.gov/fe/science-innovation/oil-gas-research/enhanced-oil-recovery> [Accessed 3 May 2021].
2. Jansen, J.D. and Durlofsky, L.J., 2017. Use of reduced-order models in well control optimization. Optimization and Engineering, 18(1), pp.105-132.
3. Jansen, J.D., Bosgra, O.H. and Van den Hof, P.M., 2008. Model-based control of multiphase flow in subsurface oil reservoirs. Journal of Process Control, 18(9), pp.846-855.
4. Lie, K.A., 2019. An introduction to reservoir simulation using MATLAB/GNU Octave: User guide for the MATLAB Reservoir Simulation Toolbox (MRST). Cambridge University Press.
5. Mathworks.com. 2021. Choosing the Algorithm- MATLAB & Simulink. [online] Available at: <https://www.mathworks.com/help/optim/ug/choosing-the-algorithm.html> [Accessed 3 May 2021].
6. Muggeridge, A., Cockin, A., Webb, K., Frampton, H., Collins, I., Moulds, T. and Salino, P., 2014. Recovery rates, enhanced oil recovery and technological limits. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 372(2006), p.20120320.
7. Uzoho, C.U., Onyekonwu, M. and adnAkaranta, O., 2015, August. Formulation of Local Alkaline-Surfactant-Polymer (ASP) For Enhanced Oil Recovery in Niger Delta: A Review. In SPE Nigeria Annual International Conference and Exhibition. Society of Petroleum Engineer
8. Zandvliet, M., Handels, M., van Essen, G., Brouwer, R. and Jansen, J.D., 2008. Adjoint-based well-placement optimization under production constraints. Spe Journal, 13(04), pp.392-399.
9. Zandvliet, M.J., Bosgra, O.H., Jansen, J.D., Van den Hof, P.M.J. and Kraaijevanger, J.F.B.M., 2007. Bang-bang control and singular arcs in reservoir flooding. Journal of Petroleum Science and Engineering, 58(1-2), pp.186-200.