



Innovative Optimization Method Increases Rate of Success to 91% on a Low Salinity Waterflood Development Plan

Benefits

- Minimize risk with a well-defined & optimized field development strategy
- Reliably forecast a reservoir's recovery factor under reservoir and operational uncertainty
- Accurately predict probability of reservoir success with reduced risk
- Rigorously analyze geological uncertainty to easily justify a profitable development plan

To succeed in today's volatile oil and gas industry; companies mitigate risk through simulation and optimization methods. Reservoir characteristics and recovery methods are becoming more complex, while conventional non-simulation methods are far too simplistic and make several assumptions that may not be true representations of the reservoir conditions. Simulation provides a platform that can be used to test a wide range of geological scenarios to identify potential operating schemes and parameters before implementing a costly field development plan.

In reservoir optimization, geological uncertainties normally have significant impact on reservoir performance. Due to this, the common strategy of obtaining an optimal solution based on a single geological realization (Nominal Optimization) may lead to inaccurate results. Consequently, a new strategy called Robust Optimization has been developed using CMOST™ AI, in conjunction with CMG's reservoir simulators - IMEX™, GEM™, STARS™ - in order to take the influence of geological uncertainty into account when creating a development plan. Robust Optimization is a practical workflow that significantly reduces computational cost by using a set of representative realizations, and is able to account for the reservoir's overall geological uncertainties.

What is Robust Optimization?

Robust Optimization takes geological uncertainty into account, by considering 100+ realizations in combination with other optimization parameters in an attempt to find a risk-weighted solution that will work for all scenarios. Robust Optimization considers from the worst to the best case geological scenarios, resulting in a development plan that eliminates any surprises when implemented in the field. This rigorous optimization method significantly reduces risk and increases the probability of success.

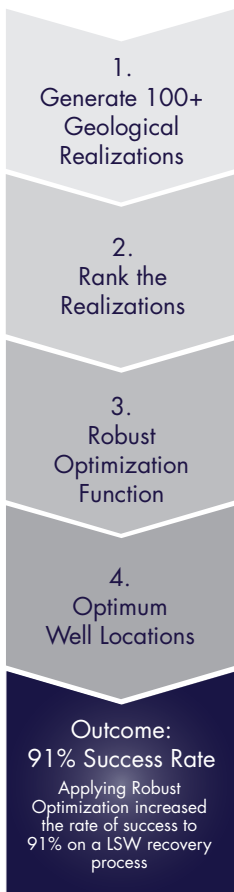
The Robust Optimization workflow was applied to an oil-wet reservoir with a goal of increasing oil production using a Low Salinity Waterflood (LSW) recovery method. LSW helps increase oil recovery by changing the wettability from oil-wet to water-wet due to sodium and calcium ion-exchange on the clay surface. Since ion-exchange on the clay surface is an important part of the process; the clay and facies distribution will impact the overall oil recovery factor. In CMOST AI, both Robust and Nominal Optimization methods were applied to the oil-wet reservoir to optimize the well location and determine the highest possible Recovery Factor (RF).

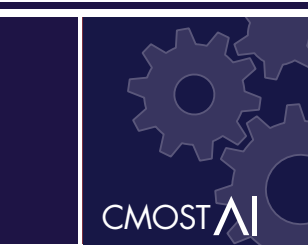
Step 1: Generate 100+ Geological Realizations

For Robust Optimization to work properly, many geological realizations need to be created where the properties being varied are the ones with the highest degree of uncertainty. In this particular oil-wet reservoir, the most important parameter with the highest degree of uncertainty was the clay distribution inside the reservoir. Clay distribution has a significant impact on the results from an LSW process and it is a widely unknown parameter. Hence, 100+ realizations were generated accounting for variability in the clay distribution in the reservoir.

Step 2: Rank the Realizations

Simulation models with all the geological realizations were run with an identical well configuration and operating strategy. The Recovery Factor (RF) from all the cases were plotted on the same chart. After reviewing the RF distribution, five representative geological realizations – P5, P25, P50, P75, and P95 – were selected and ranked, based on the probability of RF occurrence. The representations should account for the realizations with both a very high and a very low RF. The main goal of this step was to account for uncertainty in the property distribution and its impact on the results.





Step 3: Robust Optimization Function

The five representative geological realizations were taken into CMOST AI and a user-created Robust Optimization objective function was applied to optimize the production and/or recovery from all the selected cases. For the oil-wet reservoir, the following robust objective function was used:

$$J_{RO} = \bar{J} = \frac{1}{N_R} \sum_{i=1}^{N_R} J(\vec{x}, \theta_i)$$

Diagram illustrating the Robust Objective Function (RF) calculation. The formula shows the average of the objective function J over N_R realizations. The diagram includes boxes for 'Average RF Over 5 Realizations', 'Objective Function: 5 f(Parameters, Realization)', and 'Number of Realizations: 5'. A box labeled 'Robust Objective Function (RF)' points to the formula with the target 'Maximize J_{RO} '.

Next, the objective function was applied to optimize the average RF between all five geological realizations. The goal of this study was to optimize the well locations, consequently CMOST AI ran all five representative realizations with the same set of potential well locations. CMOST AI applies an internal algorithm to generate the different well locations based on the results it gathers from the Robust Optimization function. The CMOST algorithm is an important aspect to the Robust Optimization workflow as it eliminates user input error or data uncertainty.

The key difference to Nominal Optimization occurred in this step because the average RF for a range of realizations was optimized, instead of only one realization. This inherent difference between the optimization methods is responsible for a higher probability of success when using Robust Optimization.

Step 4: Optimum Case

Step 3 yielded optimum well locations based on the case that had the highest average RF between the five realizations. As a result, all original geological (100+) realizations, were run with the same well locations as the case that gave the highest average RF. The results from all individual runs were plotted in an effort to see the scatter in RF between all the cases. When compared to the results from the Nominal Optimization case, there was much lower scatter in RF when Robust Optimization was used, therefore indicating a lower risk and a higher probability of success.

Results

Both Nominal and Robust Optimization methods were tested to visualize the difference in results (figure 1). The Nominal Optimization case shows only 30% of the realizations will achieve a RF of 35% or better. Whereas, the Robust Optimized well locations show more than 50% of the possible realizations would have a RF higher than 35%. Therefore, by doing Robust Optimization, the probability of success has improved by 66%.

The cumulative probability chart (figure 2) compares the success rate, which is determined by the percentage of cases greater than 32%, from both optimization methods. Robust Optimization identified a solution with a 91% success rate, as opposed to the 61% success rate when using the Nominal Optimization method. Further, there is much less scatter in the results, which can be seen by the steeper slope for the robust case. The reduction in scatter proves there is lower risk, if this strategy is implemented in the field.

Companies applying a rigorous simulation analysis, such as Robust Optimization, will achieve a greater probability of success and reduce risk.

This case study is based upon SPE 173194 "Modeling and Optimization of Low Salinity Waterflood". To read the full technical paper, please visit www.onepetro.org.

Read more: cmgl.ca/resources

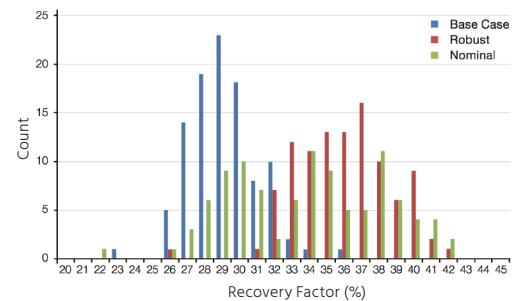


Figure 1: Distribution of Recovery Factor

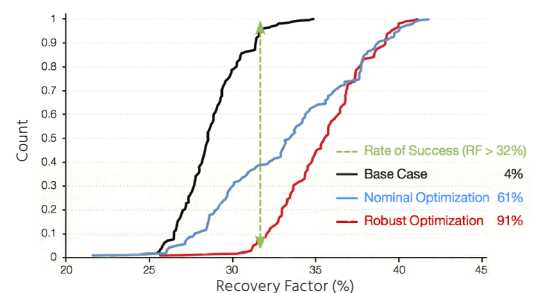


Figure 2: Success Rate of Different Optimization Methods