Olympus Challenge – Data Driven Optimization for Field Development Plan and Competition from Domain Knowledge

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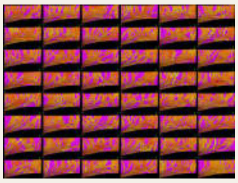
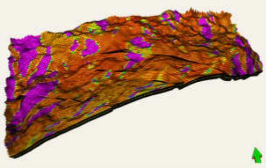
Introduction

In 2017 an industry consortium with a focus on "Integrated System Approach to Petroleum Production" (ISAPP) initiated a benchmark project on "field development optimization under uncertainty". 50 equi-probable geological realizations of a North sea like reservoir were provided to represent subsurface uncertainty.



ISAPP (Integrated Systems Approach to Petroleum Production) is a joint project of TNO, Delft University of Technology, ENI, Equinor and Petrobras.

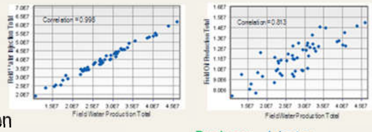


Challenge 1: Maximize **N**et **P**resent **V**alue for well control rate problem under uncertainty

Pre-evaluation: Study ensemble representation

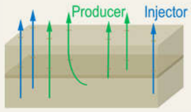
- Correlation: Injection – Production
- Voidage replacement gap

$$\frac{F_{WIT} \quad F_{OPT} \quad F_{WPT}}{F_{WIT}} \approx 2\%$$



Conclude: Optimal control parameterization

- Open/Shut wells in upper/lower formation (discrete)
- Production constraints: Max. injection and production
- Shut perforation section when impact on NPV is negative

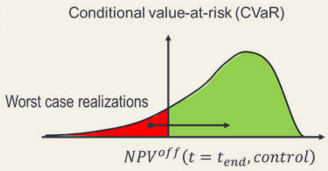


Standardized Well Control Optimization for given Field Development Plan

Objective: Optimize well control and compare results against an industry best-practice reactive control solutions over 20 year production period.

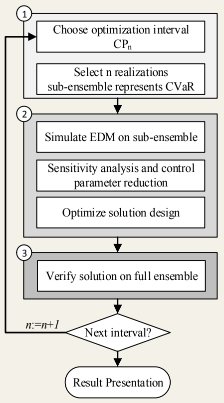
Measure: Apply an off-set distribution to measure the difference between the optimized control (*c*) and the reference solution for every realization (*i*) at different time steps (*t*)

$$NPV_i^{off}(t,c) = NPV_i^{opt}(t,c) \quad NPV_i^{ref}(t,c)$$

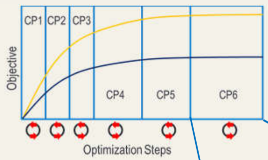


Parameterization: Perforation sections all wells.

Control setting: shut/open for each interval CP*n*

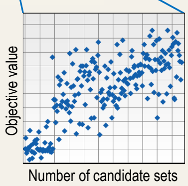


Standardized Approach: Optimize control settings based on a sequence of optimization steps.



Optimization

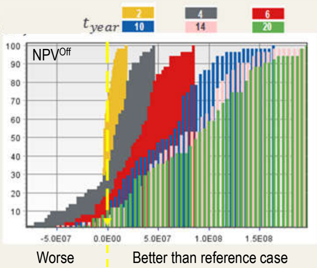
Each control interval is optimized separately.



Results for Well Control Optimization

Performance:

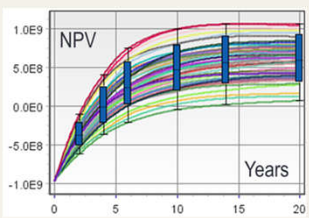
Candidate solutions outperform reference solutions at all control steps



Robustness:

Verify solution candidates for each control interval against all 50 realizations.

Negative NPV at start accounts for CAPEX.



Data Driven Optimization

Selection of representative realizations:

For all possible design configurations X the risk measure should ideally deliver the same outcome for the full ensemble calculation $Q_E(x, \boldsymbol{\rho})$ as for the selected subset of realizations $Q_E(x, \overline{\boldsymbol{\rho}})$.

In an optimization process the correlation C between the full ensemble objective $Q_E(x, \boldsymbol{\rho})$ and the corresponding reduced order ensemble objective $Q_E(x, \overline{\boldsymbol{\rho}})$ will be maximized for an arbitrarily sampled solution space X.

For a predefined dimension of the reduced order set, an optimization process is designed to select an optimal set of realizations out of the full ensemble

$$\max_{\overline{\rho}} C\left(Q_E(x, \boldsymbol{\rho}); Q_E(x, \overline{\boldsymbol{\rho}})\right)$$

Solution design:

In a sensitivity scan, control parameters are adjusted at different timesteps one-at-a-time with an impact on the economic return measured by NPV.

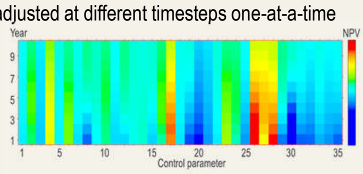
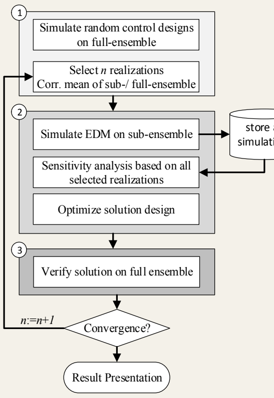


Figure: Sensitivity scan of well control parameters at different time steps with negative (blue) to positive (red) impact on NPV

Economic outcomes $Q_E(x, \overline{\boldsymbol{\rho}})$ shown for the sensitivity scan are calculated for a selected subset of realizations $\overline{\boldsymbol{\rho}}$. A performance ranking of control parameters with respect to control type and timestep is used to prioritize control parameter settings for a solution design. Starting from a baseline setting, the solution is constructed by sequentially modifying control parameter settings based on their ranking. The stability of a solution is tested by repeating sensitivity scans and constructing solutions for alternative sets of realizations with increasing ensemble size, e.g., 2,3,4, … realizations.

For the first ensemble two realizations are selected. The second ensemble is constructed by 3 new realizations plus two realizations from the first ensemble, etc.

$\overline{\rho}$	Ensemble Realizations	Size
1	ρ_{1_1}, ρ_{1_2}	2
2	$\rho_{1_1}, \rho_{1_2}, \rho_{2_1}, \rho_{2_2}, \rho_{2_3}$	3+2
3	$\rho_{1_1}, \rho_{1_2}, \rho_{2_1}, \rho_{2_2}, \rho_{2_3}, \rho_{3_1}, \rho_{3_2}, \rho_{3_3}, \rho_{3_4}$	4+5



Standardized Approach:

1) A large data set of random control design scenarios X are simulated for all realization $\boldsymbol{\rho}$. A subset of *n* realizations is selected based on an optimized correlation performance between the sub- and full-ensemble
2) Control scenarios based on a pre-defined experimental design matrix (EDM) are simulated on all new selected realizations. For re-usage in next iteration sub-ensembles, simulation outputs of all realizations are stored. In the optimization step control settings with a positive impact on the economic outcome are ranked and combined.
3) Solution scenarios are verified on the full-ensemble

Results

For this work we run 200 randomly sampled well control scenarios against 50 realizations, i.e., 10.000 full field simulation runs. The reduced order model is constructed by optimizing the correlation performance between the full ensemble and the selected realizations based on 200 well control scenarios. Over three iterations we rerun the workflow with 2, 5 and 9 realizations for constructing an optimal and robust well control design. The data-driven optimization solution outperforms the sequential schedule optimization result for both, mean NPV as well as for the offset measure.

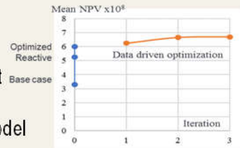


Figure: Optimized well control design over an increasing number of realizations (orange line). Reference solutions of the previous approach are shown as blue dots.

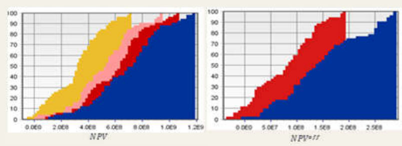


Figure: (left) basecase (yellow), reactive strategy (pink), sequential schedule optimization (red) and data driven optimization (blue). (right) NPV Offset distributions for sequential schedule optimization (red) and data driven optimization (blue) results.

Lesson Learned

Automation:

Standardized workflow designs deliver a high automation potential.

High performance computing enables optimization under uncertainty workflows.

Competition:

Domain knowledge supported by data driven analytics outperforms brute force.

Brute force is possible, but we can do better.

References:

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Schulze-Riegert, R. et al. (2018) Standardized Workflow Design For Field Development Plan Optimization Under Uncertainty. EAGE/TNO Workshop 2018 DOI: 10.3997/2214-4609.201802290