Application of Ensemble-Based Methods for Reservoir Management Decision Support

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NORCE

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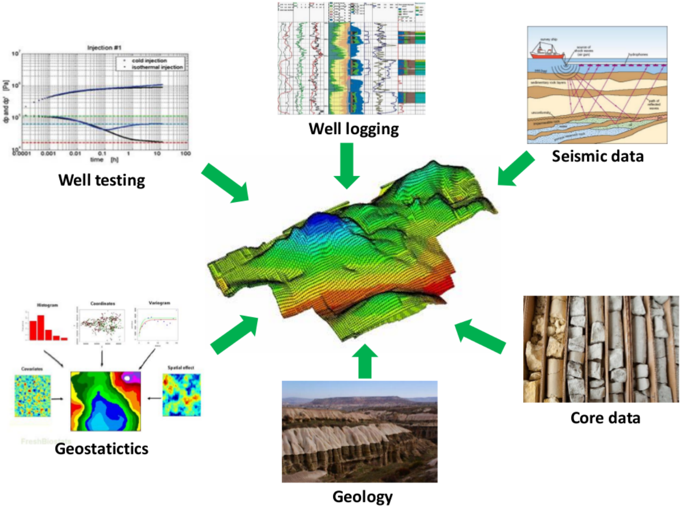
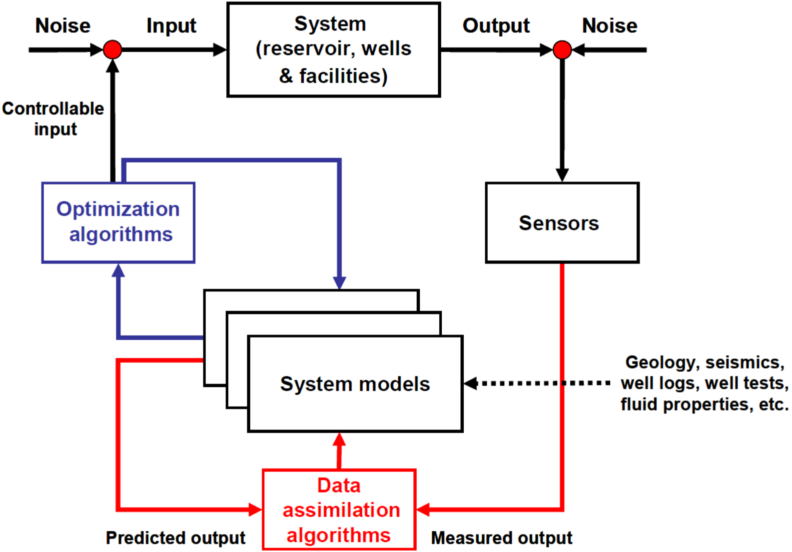
Outline

Introduction

Motivation: Reservoir Geological Uncertainty

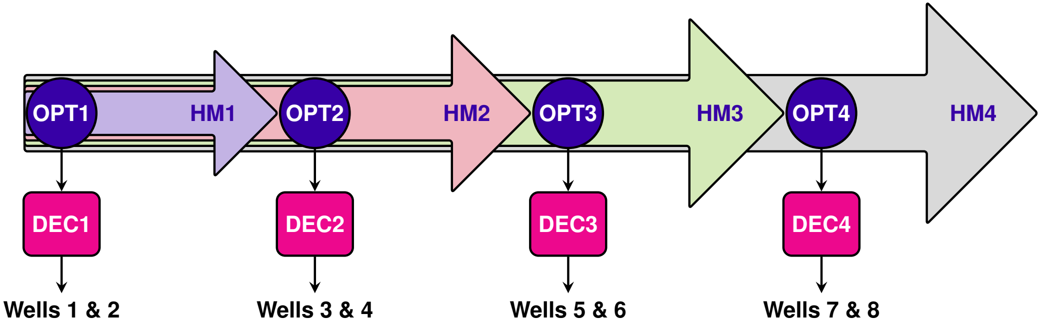


Workflow:



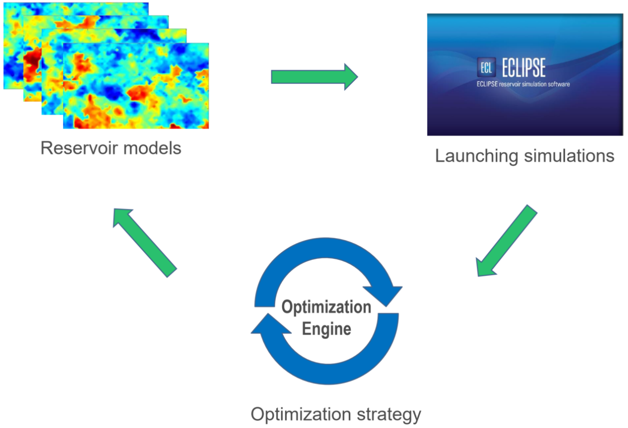
The closed-loop robust decision workflow for reservoir management (Jansen et al., 2009).

Workflow

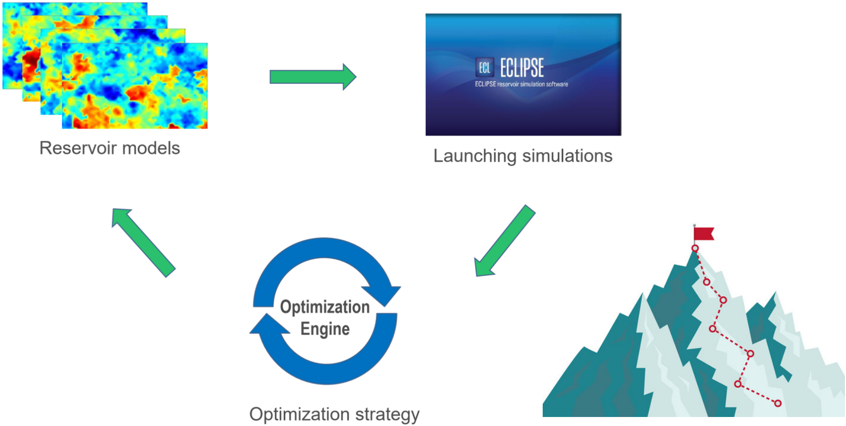


DIGIRES decision workflow for field development. Drilling two wells per year, we use the workflow to decide on the optimal drilling schedule.

Workflow


Reservoir models
ECL ECLIPSE
ECLIPSE reservoir simulation software
Launching simulations
Optimization Engine
Optimization strategy

Workflow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Optimization - Objective function

- Objective function:

$$NPV = \sum_{i=1}^{N_t} \frac{R(t_i)}{(1+d)^{t_i/\tau}},$$

- Revenue term:

$$R(t_i) = Q_{op}(t_i) \cdot r_{op} + Q_{gp}(t_i) \cdot r_{gp} - Q_{wp}(t_i) \cdot r_{wp} - Q_{wi}(t_i) \cdot r_{wi}.$$

$Q_{op}, Q_{gp}, Q_{wp}, Q_{wi}$ - rates of oil, water production and water injection.
$r_{op}, r_{gp}, r_{wp}, r_{wi}$ - corresponding prices/costs for oil, water production and water injection.
d - discount rate, t_i - report time, τ - total number of days per year.

Ensemble-based optimization (EnOpt)

- Pre-conditioned steepest ascend:

$$x^{k+1} = x^k + \eta^k C_{xx} \nabla f(x^k)$$

- Gradient approximation with geological uncertainty:

$$C_{xx} \nabla f(x) \approx \frac{1}{N_e} \sum_{j=1}^{N_e} [f(x_j, m_j) - f(\bar{x}, m_j)][x_j - \bar{x}]$$

- For more information we refer to:
  Chang et al. (2019), Stordal et al. (2016), Chen et al. (2009)

HM - Subspace EnRML

- An updated ensemble realization, x_j^a:

$$x_j^a = x_j^f + Aw_j,$$

- The cost function in the Ensemble Subspace:

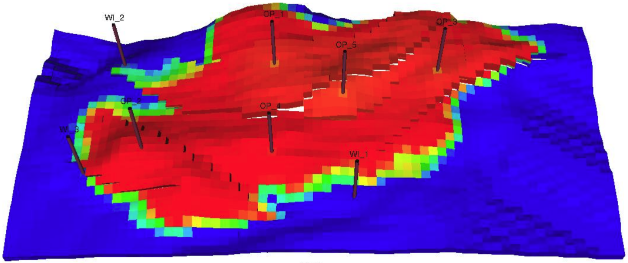
$$J(w_j) = \frac{1}{2} w_j^T w_j + \frac{1}{2} \left(g(x_j^f + Aw_j) - d_j \right)^T C_{dd}^{-1} \left(g(x_j^f + Aw_j) - d_j \right).$$

x_j^f - the prior realization. w_j - the ensemble anomaly.

- For more information we refer to:
  Evensen et al. (2019), Evensen (2021).

Case I: Closed-loop reservoir management

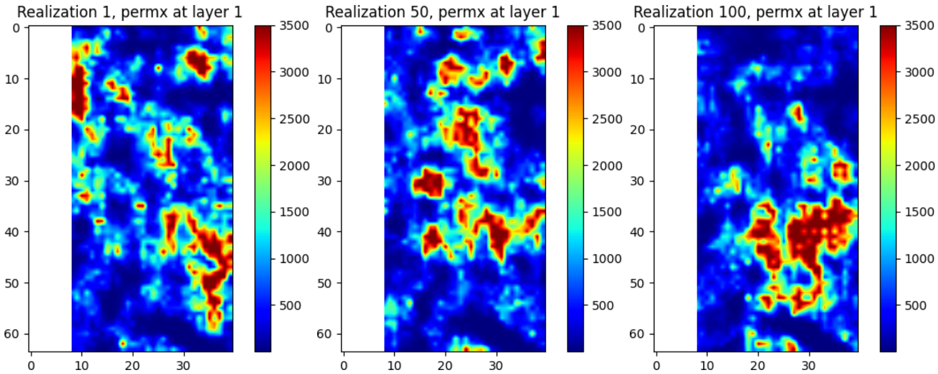
Introduction - REEK Case



Reek Model:

- Model size: $40 \times 64 \times 14$
- Wells: 5 producers, 3 injectors.
- Control mode: BHP (producers), BHP (injectors).
- Yearly recursive model update: 12 months $\times$ 5 years.
- Geological realizations: 100

Selected geological realizations



Permeability of Layer 1 on selected geological realizations and the mean model.

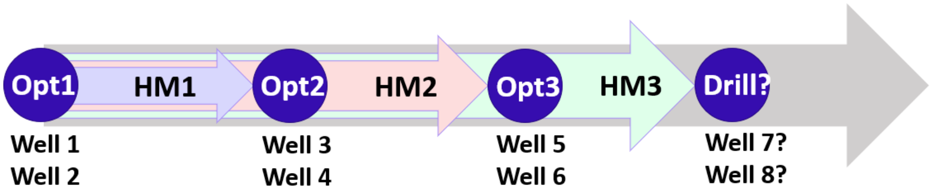
Optimization Settings

- EnOpt with backtracking is applied, $N = 100$.
- Control variables are drilling priorities of 8 wells.
- The starting point of drilling priorities follows uniform distribution, $X \sim U(0, 1)$.
- The initial value for the stepsize is 0.1 and for the ensemble perturbation covariance is 0.01.

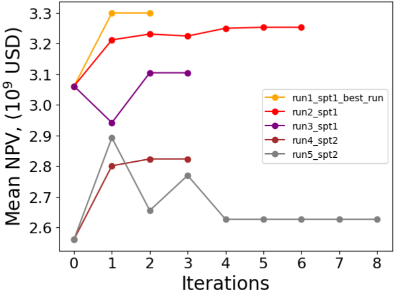
History Matching Settings

- Subspace EnRML is applied, number of realizations $N = 100$.
- Observations: WOPR, WGPR, WWPR of producers and WWIR of injectors.
- Observation error: relative variance is 5%, absolute variance is 64 for WOPR and WWPR, 1e4 for WGPR and 25 for WWIR (for observation values lower than 10).
- Parameter boundries: PERMX $\sim [e^{-5}, e^{7.5}]$, PORO $\sim [0.001, 0.5]$, MULTFLT $\sim [0, 0.7]$.

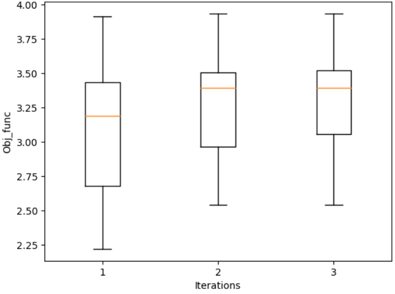
Decision Stages - Optimization



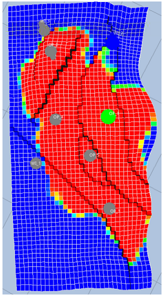
OPT1 - Optimization of the Decision Stage 1



Mean NPV vs. iter



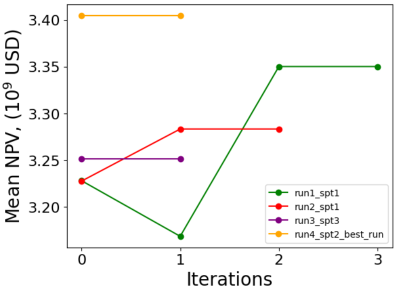
NPVs of the best run



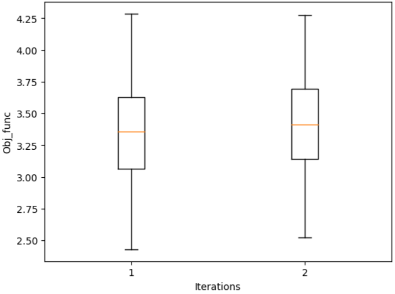
Decision

Optimization of the Decision Stage 1. Wells OP-1 and WI-2 are drilled after the optimization.

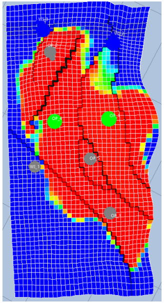
OPT2 - Optimization of the Decision Stage 2



Mean NPV vs. iter



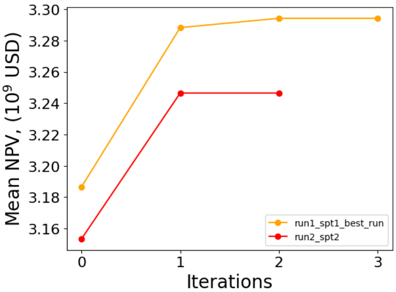
NPVs of the best run



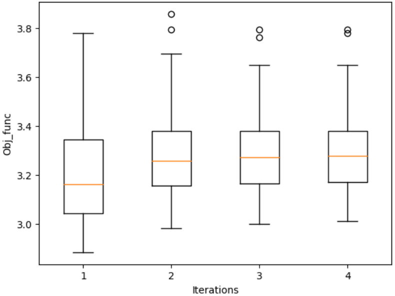
Decision

Optimization of the Decision Stage 2. Wells OP-4 and WI-3 are drilled after the optimization.

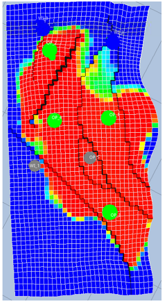
OPT3 - Optimization of the Decision Stage 3



Mean NPV vs. iter



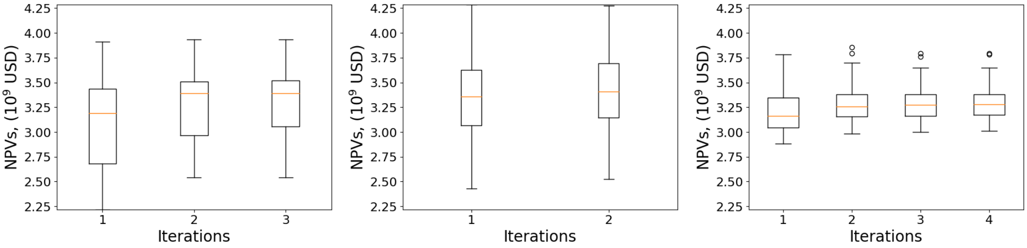
NPVs of the best run



Decision

Optimization of the Decision Stage 2. Wells OP-2 and OP-3 are drilled after the optimization.

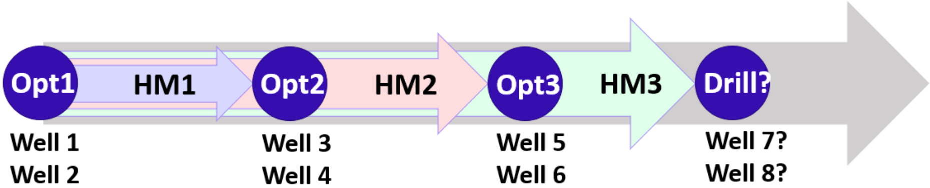
Summary - Uncertainty of optimization steps



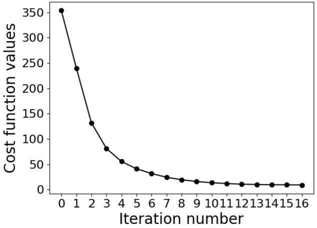
(a) OPT1 (b) OPT2 (c) OPT3

Uncertainty is reduced during the workflow.

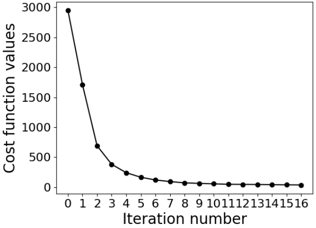
Decision Stages - History Matching



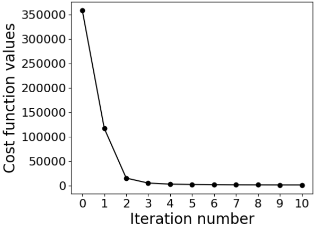
Summary - Cost function values of history matching steps



(a) HM1



(b) HM2



(c) HM3

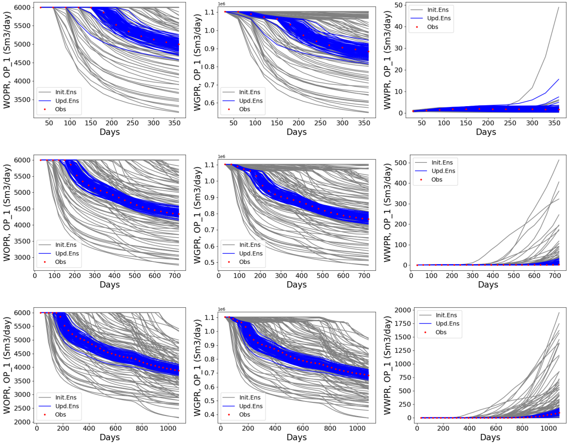
Data mismatch is reduced during the workflow.

Summary - Production profiles for OP-1

HM1

HM2

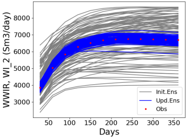
HM3



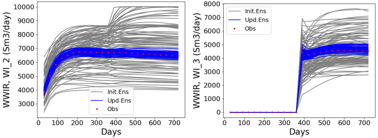
Production profiles for OP-1 following the different history matching steps **HM1** (upper), **HM2** (middle), and **HM3** (lower).

Summary - Production profiles for WI-2 and WI-3

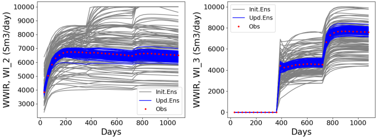
HM1



HM2

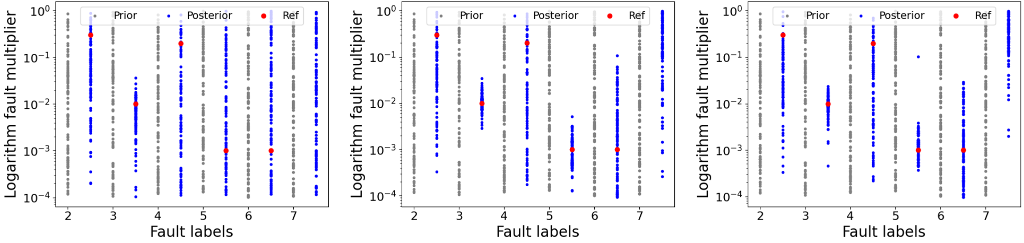


HM3



Injections rates of WI-2 (left) and WI-3 (right) following the three history-matching steps **HM1** (upper), **HM2** (middle), and **HM3** (lower).

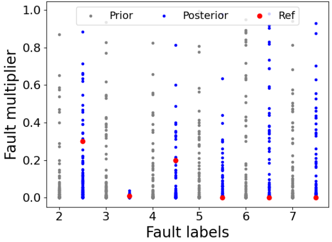
MULTFLT updates - Logarithm scale



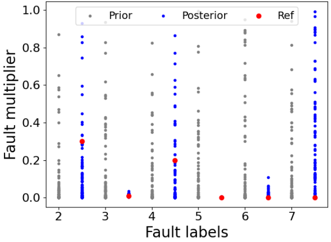
(a) HM1 (b) HM2 (c) HM3

Fault multiplier updates for all history matching steps. Grey, blue and red circles represent prior, posterior and reference values.

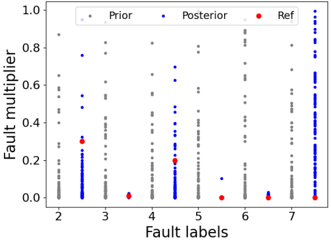
MULTFLT updates - Original scale



(a) HM1



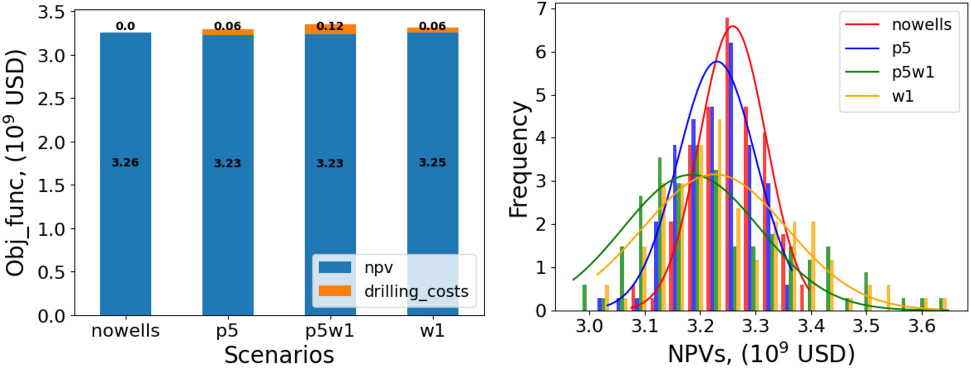
(b) HM2



(c) HM3

Fault multiplier updates for all history matching steps. Grey, blue and red circles represent prior, posterior and reference values.

Decision on the last two wells



Comparison of the four decision scenarios on whether to drill the last two wells.

Case II: Efficient optimization using a mean model

Motivation

- Number of simulations required:
  - Opt. on all geo-models: $N_{sim} = N_{iter} \times (2N_e)$, with $N_e = N_m$ for EnOpt method (Fonseca et al., 2017).
  - Opt. on the mean model: $N_{sim} = N_{iter} \times (N_e + 1) + N_m$.

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- Example of computational efforts with $N_m = 100$:

N_{iter}	Opt. on all geo-models $N_{sim}(N_e = 100)$	Opt. on the mean model $N_{sim}(N_e = 30)$	Opt. on the mean model $N_{sim}(N_e = 100)$
20	**4000**	$31 \times 20 + 100 = 720$	$101 \times 20 + 100 = 2120$
50	10000	$31 \times 50 + 100 = 1650$	$101 \times 50 + 100 = 5150$

Number of simulations required for each optimization scenarios.

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Number of simulations required for each optimization scenarios.

- **Goal: Achieve better optimal solutions with less computational effort!**

Estimation of expected value (Wang and Oliver, 2020)

- Average NPV over an ensemble of reservoir models:

$$E[f(x,m)] = \bar{f}(x) = \frac{1}{N_m}\sum_{j=1}^{N_m} f(x,m_j) \tag{1}$$

- Value from the mean model (averaged uncertain parameters):

$$f(x,E[m]) = f(x,\overline{m}) \tag{2}$$

Note that $f(x,E[m]) \neq E[f(x,m)]$.

- Estimation of average NPV from the mean model with a multiplicative correction factor:

$$\bar{f}(x_i) = \alpha(x_i) f(x_i,\overline{m}) \tag{3}$$

$$\alpha(x_i) = \frac{1}{N_m}\sum_{j=1}^{N_m}\frac{f(x_i,m_j)}{f(x_i,\overline{m})} = \frac{1}{N_m}\sum_{j=1}^{N_m}\beta_{ij} \tag{4}$$

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Estimation of correction factor α

- Random samples of controls and model realizations:

$$\mathbf{b} = [\beta_{11}, \beta_{22}, \cdots, \beta_{N_m N_m}]^T, \beta_{ii} = \beta(x_i, m_i) = \frac{f(x_i, m_i)}{f(x_i, \overline{m})} \quad (5)$$

- Approaches
  - Estimate the mean value of the correction factor:

$$\overline{\alpha} \approx \frac{1}{N_m} \sum_{j=1}^{N} \beta(x_j, m_j) \quad (6)$$

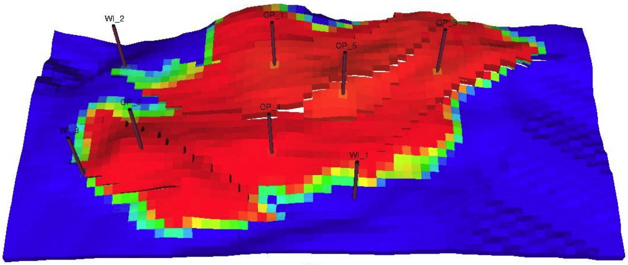
  - Distance-based localization:

$$\hat{\alpha}(x_i) = \frac{\sum_{j=1}^{N_m} \omega(x_i, x_j, L)\beta(x_j, m_j)}{\sum_{j=1}^{N_m} \omega(x_i, x_j, L)} \quad (7)$$

    where, L is the taper length, ω is the weight calculated based on the distance between x_i and x_j.

- See Wang and Oliver (2020) for more details.

Introduction - REEK Case



Reek Model:

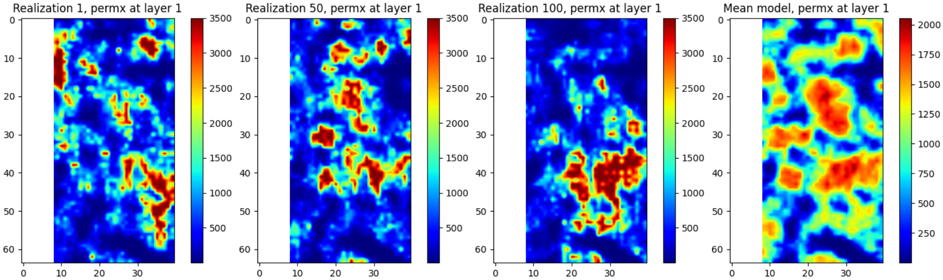
- Model size: $40 \times 64 \times 14$
- Wells: 5 producers, 3 injectors.
- Control parameters to optimize: WOPR (producers), WWIR (injectors) every six months during 10 years of production period.
- Geological realizations: 100

Mean model for REEK

Settings:

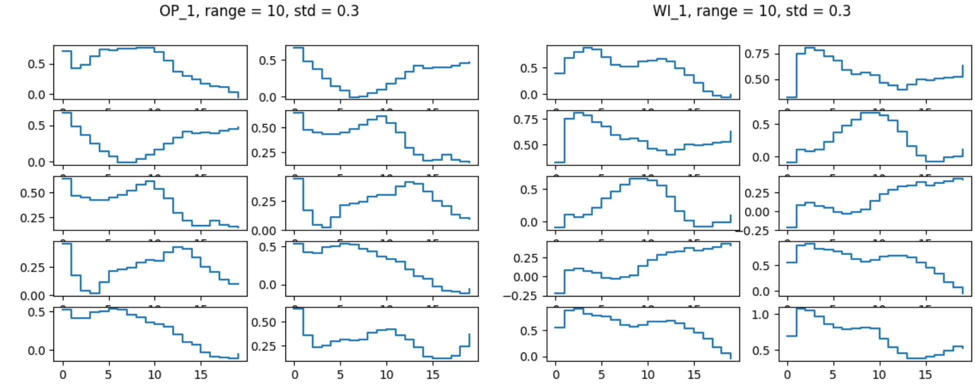
- Arithmetic mean of porosity, fault multipliers and log(PERMX) are used as the mean model.
- Control variables are oil rates for producers and injection rates for injectors.
- 100 control strategies are generated by perturbing the reference rates.
- Each control strategy is evaluated on one realization (1to1) and the mean model to get "observed" NPVs (training set).
- Size of the training set: 100.
- Size of the testing set: 100.

The mean model



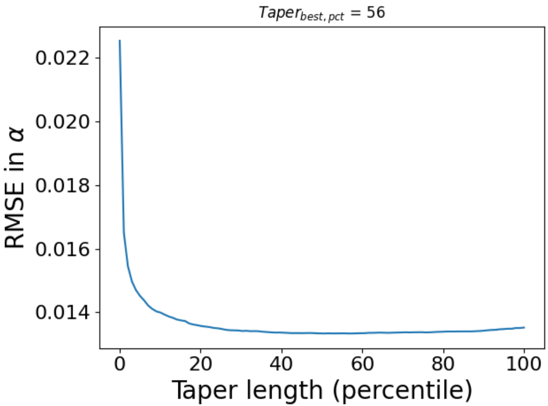
Permeability of Layer 1 on selected geological realizations and the mean model.

Well rate training samples (scaled data)



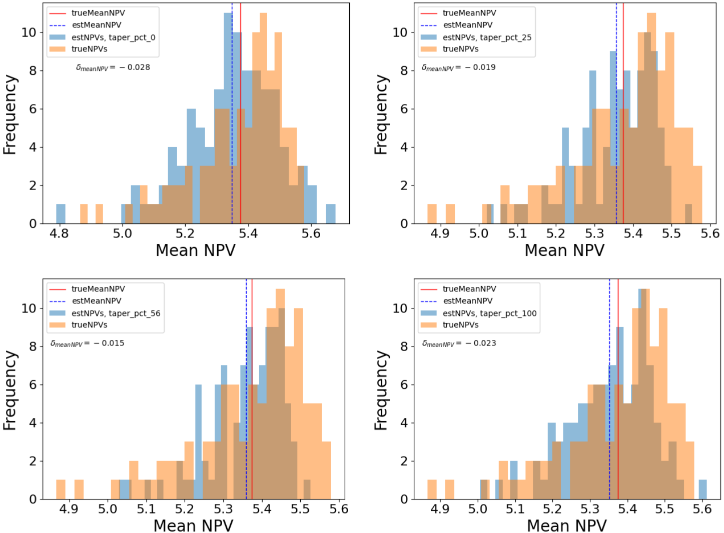
Selected examples of training samples.

Localization of bias correction factor α

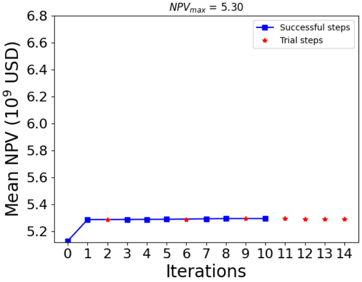


100 new control strategies are generated as a testing set.

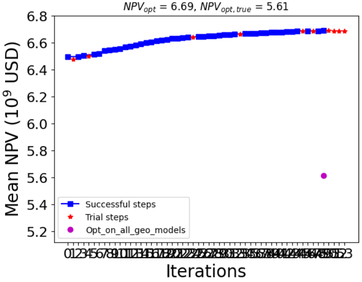
Distribution of NPV at different taper length



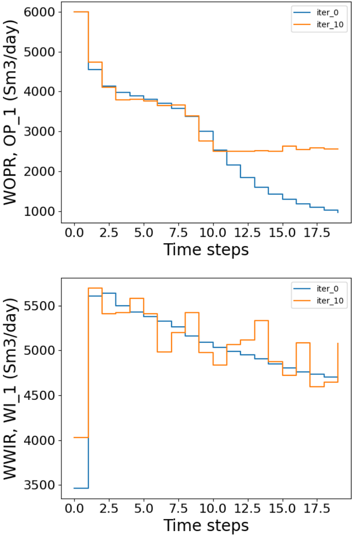
Optimization performance



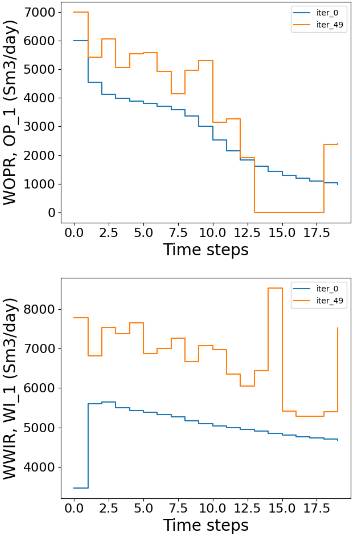
EnOpt on all models ($N_{sim} = 3000$)



EnOpt on the mean model ($N_{sim} = 1774$)



EnOpt on all models ($N_{sim} = 3000$)



EnOpt on the mean model ($N_{sim} = 1774$)

Summary

- The concept of combining optimization and history matching as a decision-making workflow is demonstrated on the REEK case.
- Multiple starting points help the optimization algorithm to find solutions that are closer to the global optimum.
- History matching helps to update the model and achieve better understanding on model uncertainty, which can assist the optimization step to obtain more robust solutions.
- Performing optimization and history matching iteratively provides decision-makers better tools for reservoir management.
- The preliminary study show that the mean-model bias-correction method helped to find a better solution with less computational effort.

Acknowledgement

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The study of Case II received financial support from Equinor Energy AS.

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Thank you