National IOR Center Workshop on Production optimization, value of information and decision-making

September 7-8, 2021 (virtual event)

Participants: IOR center participants, invited guests from academia.

Tuesday September 7

12.00: Welcome and introduction, Randi Valestrand, NORCE

Session 1

Decision Making under Uncertainty for Reservoir Management

12.15: Remus Hanea, Equinor: "Decision Optimization – an ensemble based multi-objective decision support framework"

12.45: Yuqing Chang and Geir Evensen, NORCE: "The DIGIRES workflow for ensemble-based decision making"

13.15: Aojie Hong, UiS: "Impact of Risk Attitude on Reservoir Management Decisions"

13.45: Break, 45 minutes

Session 2

Probabilistic Production Forecasting

14.30: Eivind Bakken, Equinor "Fit-for-purpose forecasting in Equinor"

15.00: Reidar Bratvold, UiS: "NCS production forecasts: Optimistic and overconfident, over and over again."

15.30: Break, 15 minutes

15.45: Erik Nesvold, UiS, "Empirical bias correction of oil production forecasts on the NCS"

16.15: Vedad Hadziavdic, Wintershall Dea: "Forecasting and field management using ensemble models – benefits and challenge"

Wednesday September 8

Session 3

Efficient and Robust Production Optimization under Uncertainty

12:00: Jan Dirk Jansen, TU Delft: “Historical developments in production optimization (from a reservoir-engineering perspective)”

12.30: Olwijn Leeuwenburgh, TU Delft & TNO: “Ensemble optimization – theory and applications”

13.00: Break 15 min.

13.15: Yuqing Chang, NORCE, “Robust and efficient optimization demonstrated on the Olympus field”.

13.45: Micheal Oguntola, UiS/NORCE: “Production optimization methodology and applications for EOR”

14.15: Break, 15 minutes

Session 4

Value of Data, Information and Knowledge

14.30: Thierry Laupretre, AkerBP: ”Value and challenges of uncertainty centric workflows in AkerBP”

15.00: Andre Morosov, UiS: “Decide to use data or use data to decide?”

15.30: Jo Eidsvik, NTNU: “Monte Carlo simulation plus machine learning methods for Value-of-Information calculations”

16.00: Randi Valestrand: Concluding remarks & fare well

DIGIRES Concept Demonstrated on the REEK Case

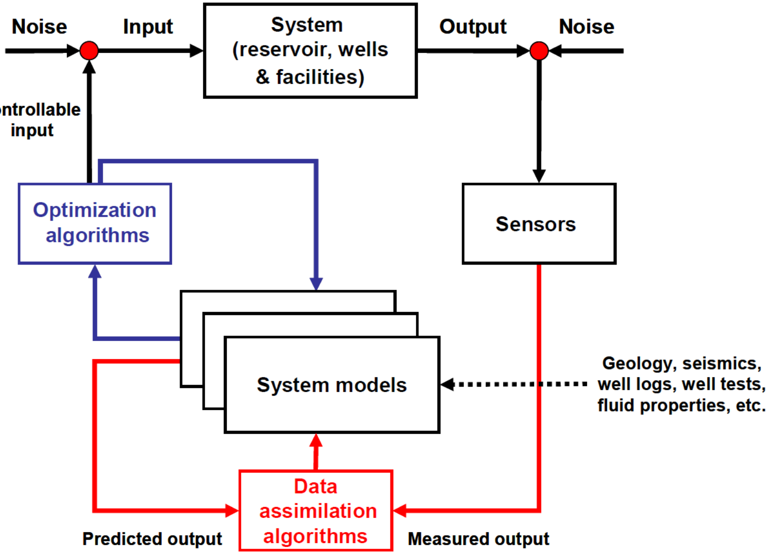
Yuqing Chang

NORCE

IOR Centre Workshop on production optimization, value of information and decision-making
7-8 September, 2021

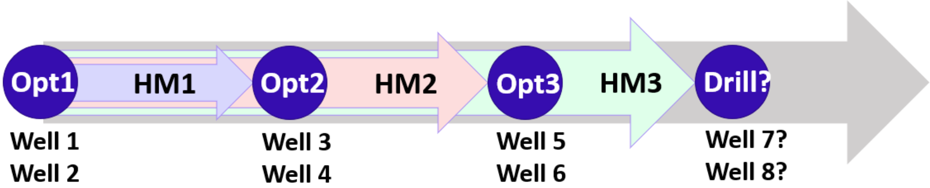
Introduction

Workflow:



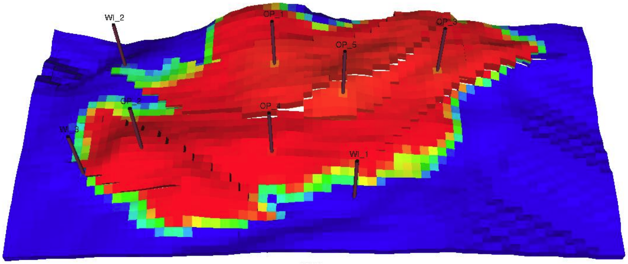
The closed-loop robust decision workflow for reservoir management (Jansen et al., 2009).

Workflow



Workflow of DIGIRES Concept.

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

Optimization - Objective function

- Objective function:

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

- Revenue term:

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

Q_{op}, Q_{wp}, Q_{wi} - rates of oil, water production and water injection.
r_{op}, 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:

$$x_{k+1} = x_k + \eta_k C \nabla J_k$$

- Gradient approximation with geological uncertainty:

$$\nabla J_k \approx N^{-1} \sum_{i=1}^{N} [J(x_k^i, y^i) - J(x_k, y^i)][x_k^i - x_k]$$

- For more information we refer to:
  Chang et al. (2019), Stordal et al. (2016), Chen et al. (2009), Lorentzen et al. (2006)

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.

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).

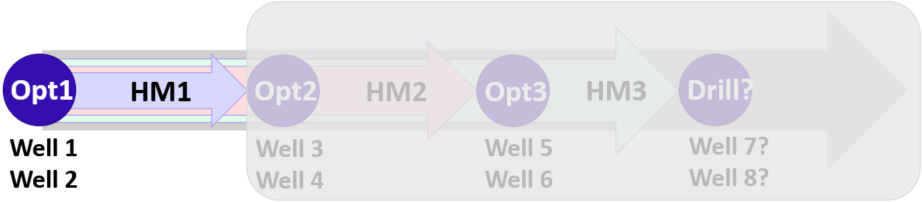
History Matching Settings

- Subspace EnRML is applied, number of realizations $N = 100$.
- Observations: WOPR, WWPR, WWIR of existing wells.
- Observation error: relative variance is 5%, absolute variance is 64 for WOPR and WWPR, 25 for WWIR (for observation values lower than 10).
- Parameter boundries: PERMX $\sim [e^{-5}, e^{8.5}]$, PORO $\sim [0.001, 0.5]$, MULTFLT $\sim [0, 0.7]$.
- Step size γ_i at iteration i:

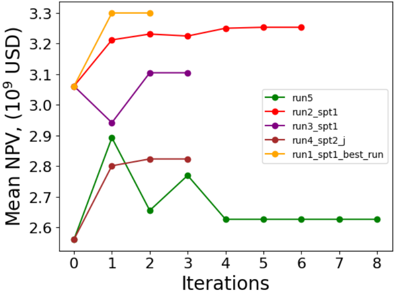
$$\gamma_i = t_2 + (t_1 - t_2) \cdot 2^{(-(i-1)/(t_3-1))},$$

where, the maximum step length $t_1 = 0.5$, the minimum step length $t_2 = 0.2$, and the step length decline factor $t_3 = 2.5$ (Evensen, 2021).

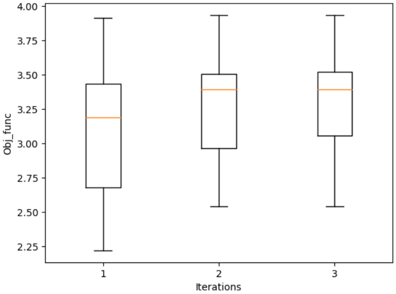
Decision Stage 1



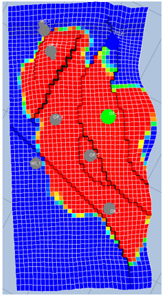
Opt1 - obj. vs. iter



Mean NPV vs. iter



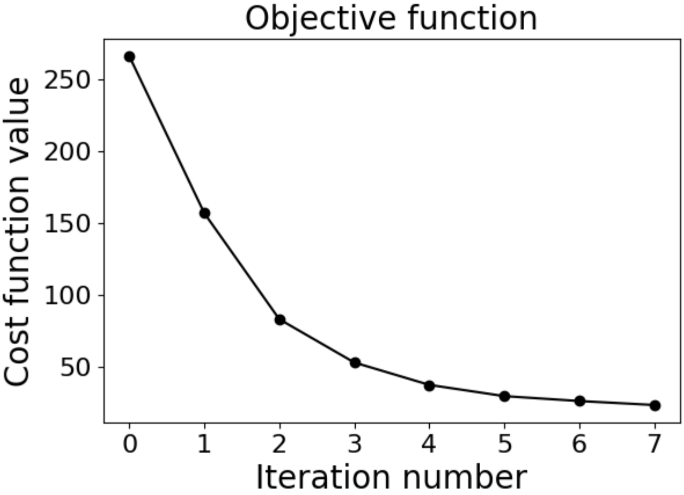
NPVs of the best run



Decision

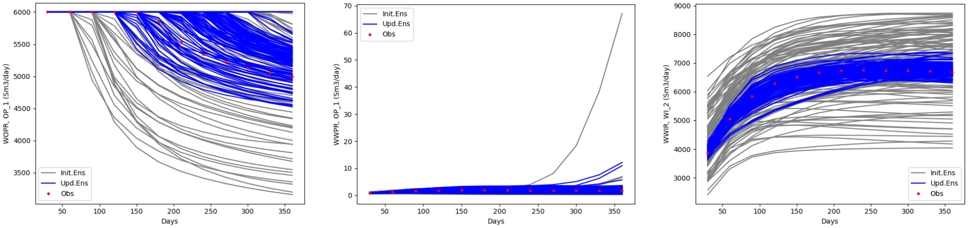
Optimization of the decision Stage 1. Wells OP-1 and WI-2 are drilled after the optimization.

HM1 - obj fn.



Objective function
Cost function value
250
200
150
100
50
0
1
2
3
4
5
6
7
Iteration number

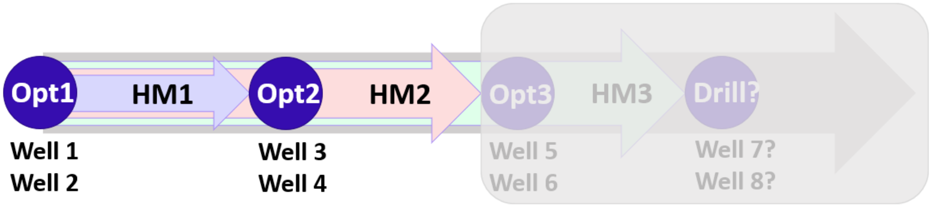
HM1 - Production profiles



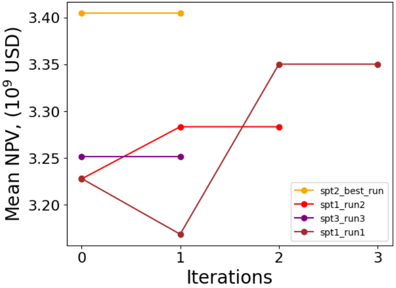
(a) WOPR, OP_1 (b) WWPR, OP_1 (c) WWIR, WI_2

Production profiles for existing wells.

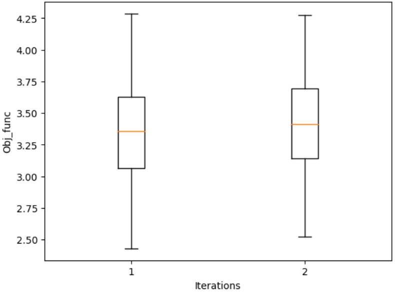
Decision Stage 2



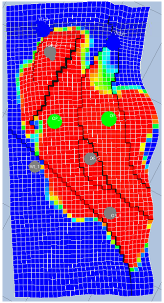
Opt2 - obj. vs. iter



Mean NPV vs. iter



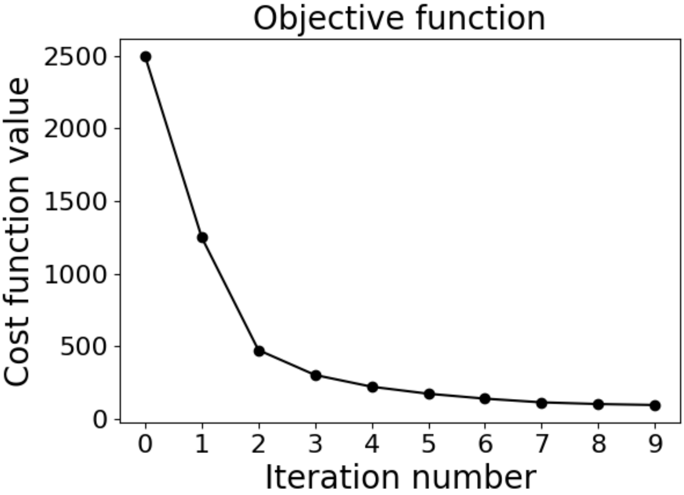
NPVs of the best run



Decision

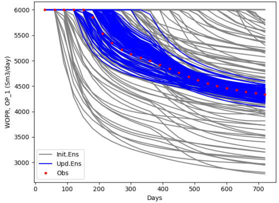
Optimization of the decision Stage 2. Wells OP-4 and WI-3 are drilled after the optimization.

HM2 - obj fn.

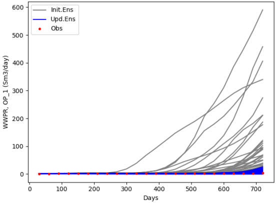


Objective function
Cost function value
2500
2000
1500
1000
500
0
0
1
2
3
4
5
6
7
8
9
Iteration number

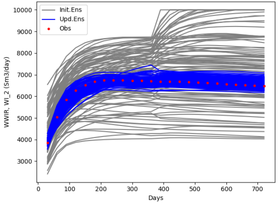
HM2 - Production profiles



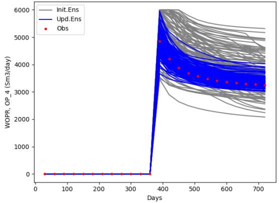
(a) WOPR, OP_1



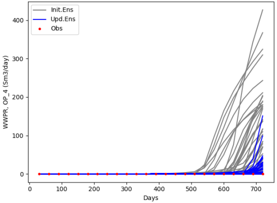
(b) WWPR, OP_1



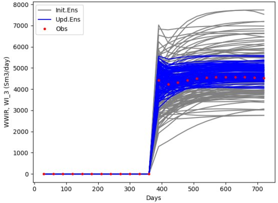
(c) WWIR, WI_2



(d) WOPR, OP_4

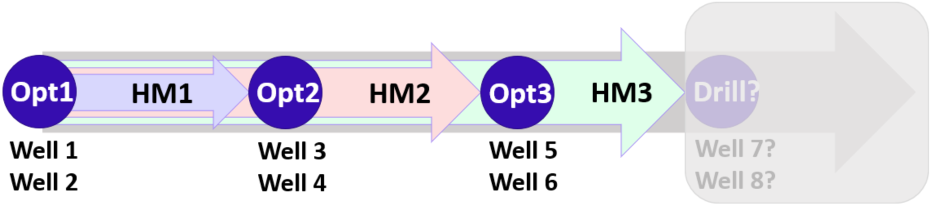


(e) WWPR, OP_4

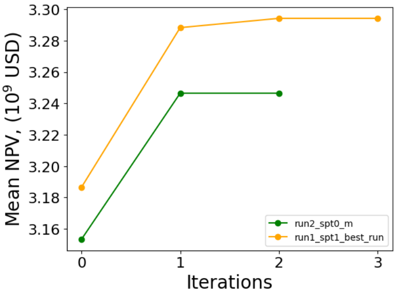


(f) WWIR, WI_3

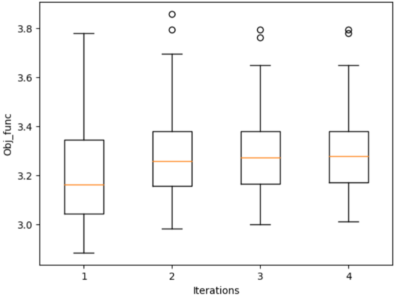
Decision Stage 3



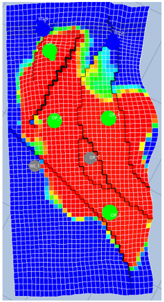
Opt3 - obj. vs. iter



Mean NPV vs. iter



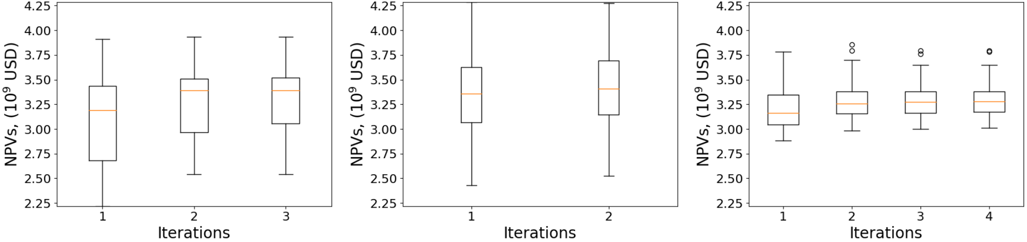
NPVs of the best run



Decision

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

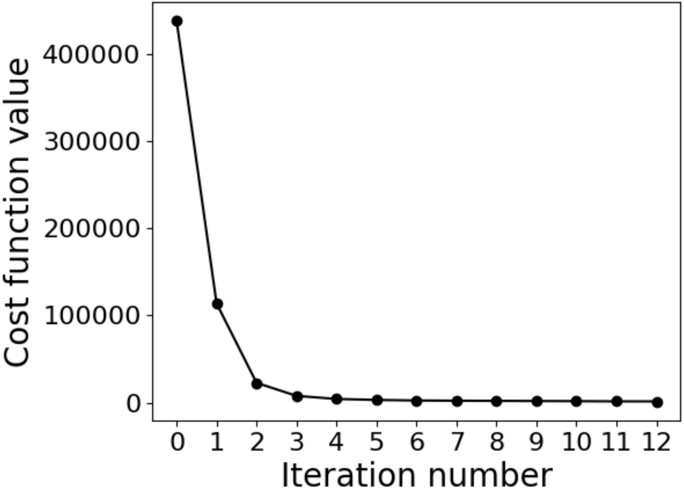
Summary - Uncertainty of optimization steps



(a) Opt1 (b) Opt2 (c) Opt3

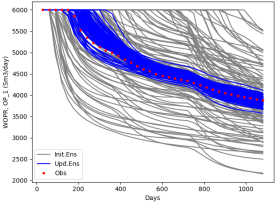
Uncertainty is reduced during the workflow.

HM3 - obj fn.

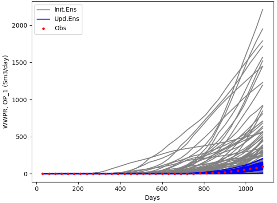


400000
300000
200000
100000
0
Cost function value
0 1 2 3 4 5 6 7 8 9 10 11 12
Iteration number

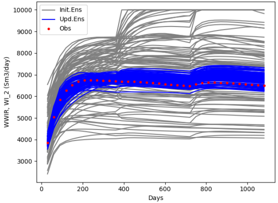
HM3 - Production profiles



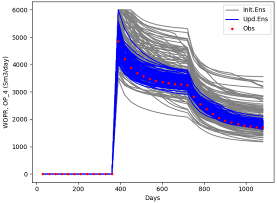
(a) WOPR, OP_1



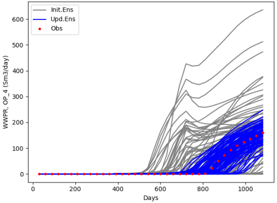
(b) WWPR, OP_1



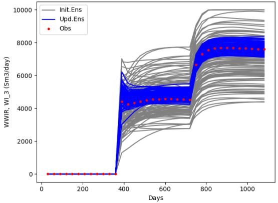
(c) WWIR, WI_2



(d) WOPR, OP_4

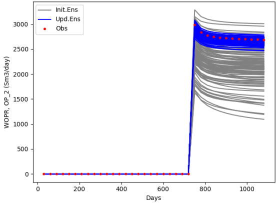


(e) WWPR, OP_4

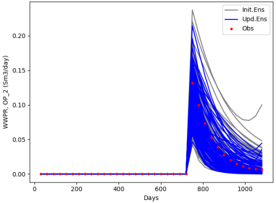


(f) WWIR, WI_3

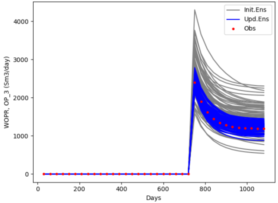
HM3 - Production profiles cont.



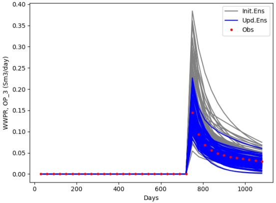
(a) WOPR, OP_2



(b) WWPR, OP_2

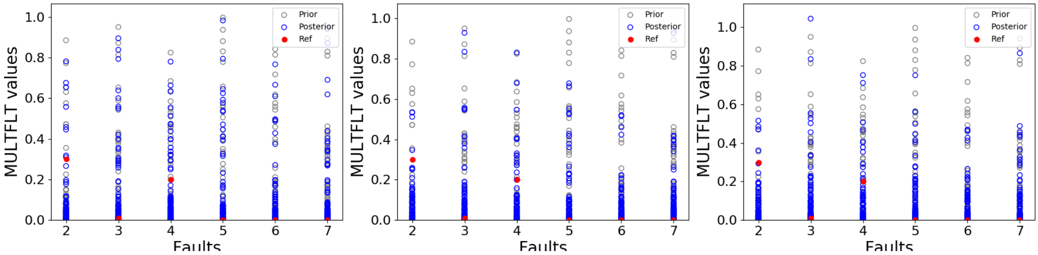


(c) WOPR, OP_3



(d) WWPR, OP_3

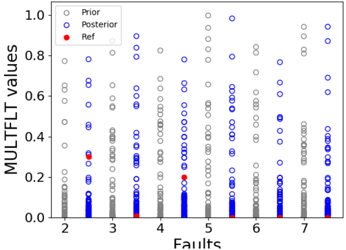
MULTFLT updates - HM steps



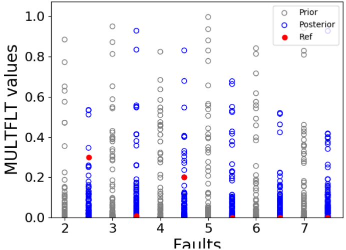
(a) HM1 (b) HM2 (c) HM3

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

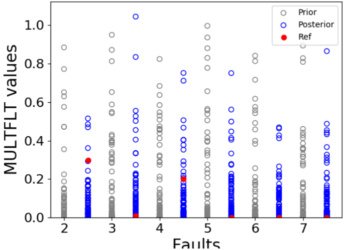
MULTFLT updates - HM steps



(a) HM1



(b) HM2

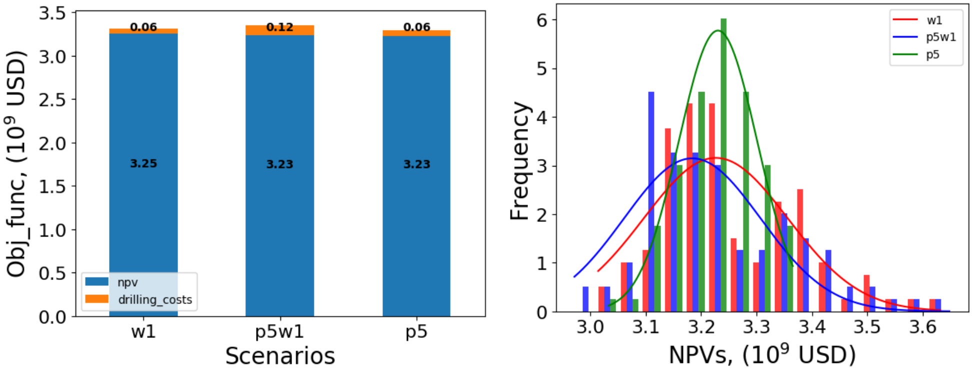


(c) HM3

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

Decision Stage

Decision on the last two wells



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

Summary

- The DIGIRES 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.

References

Chang, Y., R. J. Lorentzen, G. Nævdal, and T. Feng, OLYMPUS optimization under geological uncertainty, *Computational Geosciences*, 2019.

Chen, Y., D. S. Oliver, and D. Zhang, Efficient ensemble-based closed-loop production optimization, *SPE Journal*, **14**(2), 634–645, 2009, sPE-112873-PA.

Evensen, G., Formulating the history matching problem with consistent error statistics, *Computational Geosciences*, **25**, 945–970, 2021.

Evensen, G., P. N. Raanes, A. S. Stordal, and J. Hove, Efficient implementation of an iterative ensemble smoother for data assimilation and reservoir history matching, *Frontiers in Applied Mathematics and Statistics*, **5**, 47, 2019.

Jansen, J.-D., R. Brouwer, and S. G. Douma, Closed loop reservoir management, in *SPE Reservoir Simulation Conference*, 2009, SPE-119098-MS.

Lorentzen, R. J., A. M. Berg, G. Nævdal, and E. H. Vefring, A new approach for dynamic optimization of water flooding problems, in *SPE Intelligent Energy Conference and Exhibition*, Amsterdam, The Netherlands, 2006, paper SPE 99690.

Stordal, A. S., S. P. Szklarz, and O. Leeuwenburgh, A theoretical look at ensemble-based optimization in reservoir management, *Mathematical Geosciences*, **48**(4), 399–417, 2016.

Impact of Risk Attitude on Reservoir Management Decisions

Aojie Hong

Decision and Data Analytics Group

Department of Energy Resources

University of Stavanger

Agenda

1. How to model risk attitude?

2. What is the impact of risk attitude on reservoir management decisions in the long term?

3. How to incorporate risk attitude in ensemble-based optimization?

“A good decision is an action we take that is logically consistent with the alternatives we perceive, the information we have, and the preferences we feel.”

– Ronald A. Howard

“A good decision is an action we take that is logically consistent with the alternatives we perceive, the information we have, and <u>the preferences we feel</u>.”

– Ronald A. Howard

The petroleum industry is risk-averse in general.

Study on the 50 largest US-based oil companies from 1983 – 2002 (Walls 2005):

- All 50 companies are risk-averse.
- The larger (wealthier) a company is, the less risk-averse it is.

How to consistently account for risk-attitude in decision making?

Modeling Risk Attitude

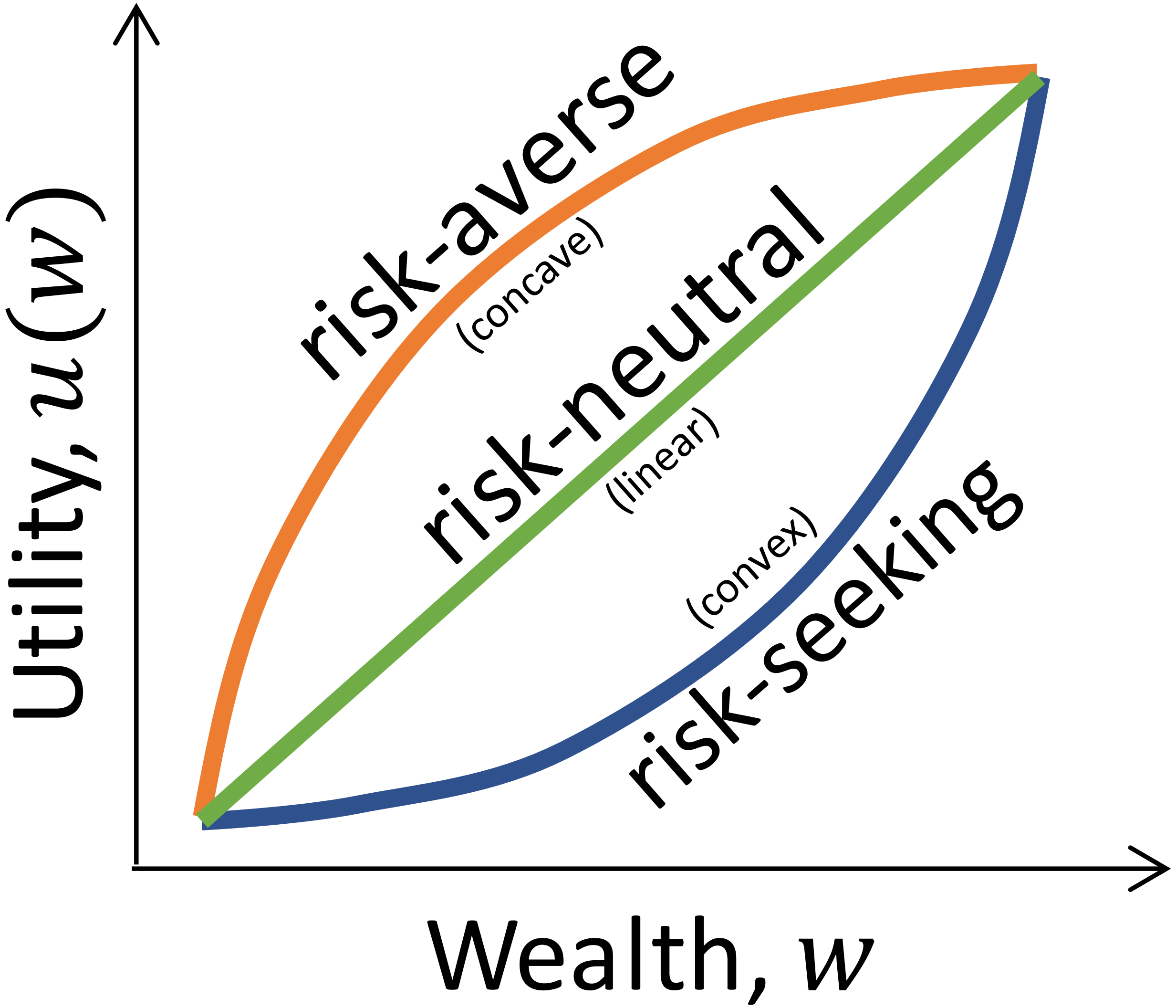
The expected utility theory is the normative model for accounting for risk attitude in rational decision making.

- Daniel Bernoulli (1738) proposed the concept of utility.

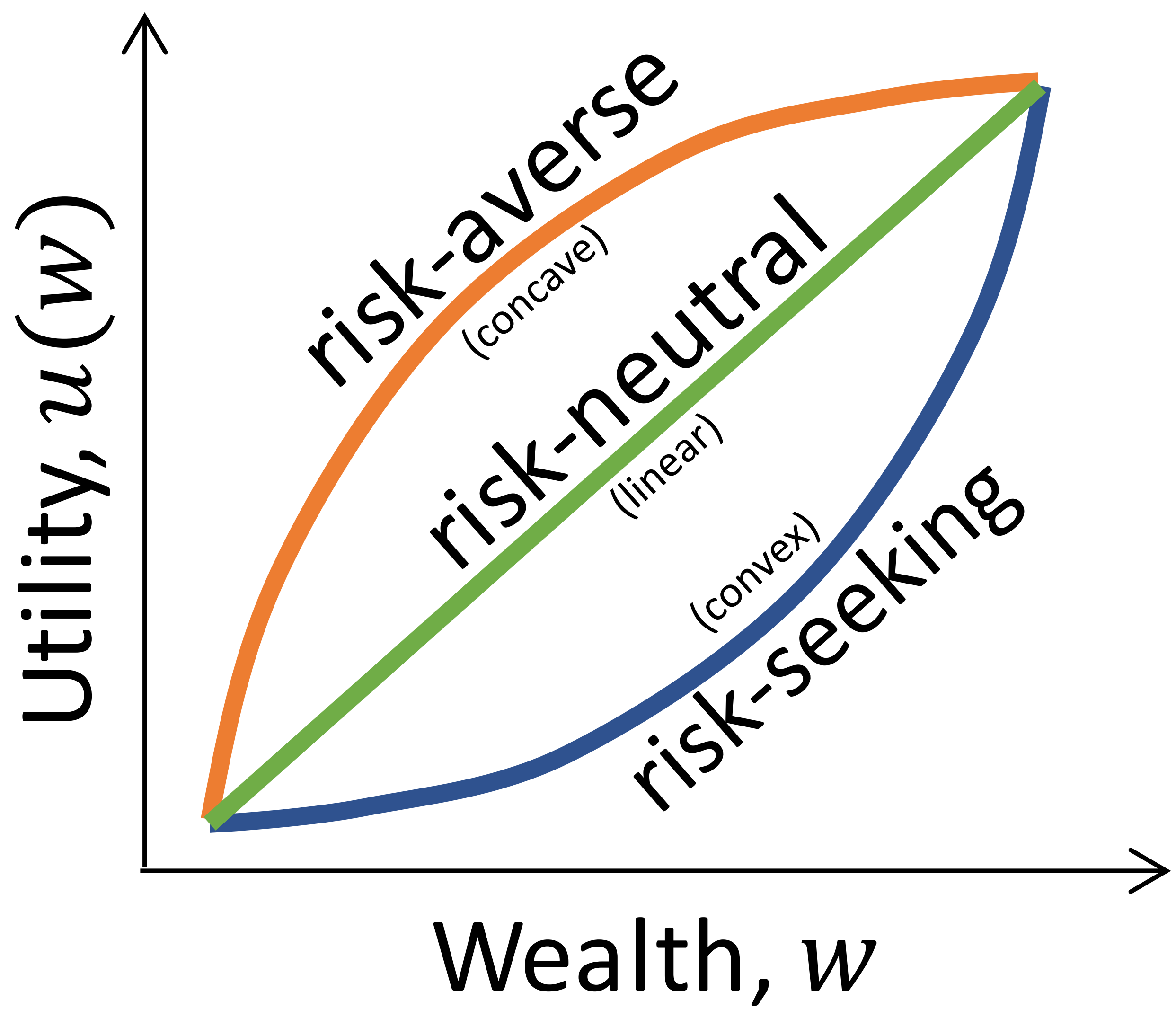
- Von Neumann and Morgenstern (1947) developed the expected utility theory (EUT) based on a few axioms/rules.
  - A rational decision maker following these rules must have a utility function.
  - A decision maker using a utility function automatically obeys these rules and will make rational decisions under uncertainty.

- EUT has been pragmatically applied in economics, decision analysis, and game theory.

Utility Functions for Risk-Averse, Neutral, and Seeking.



The objective is to maximize the expected utility (EU).



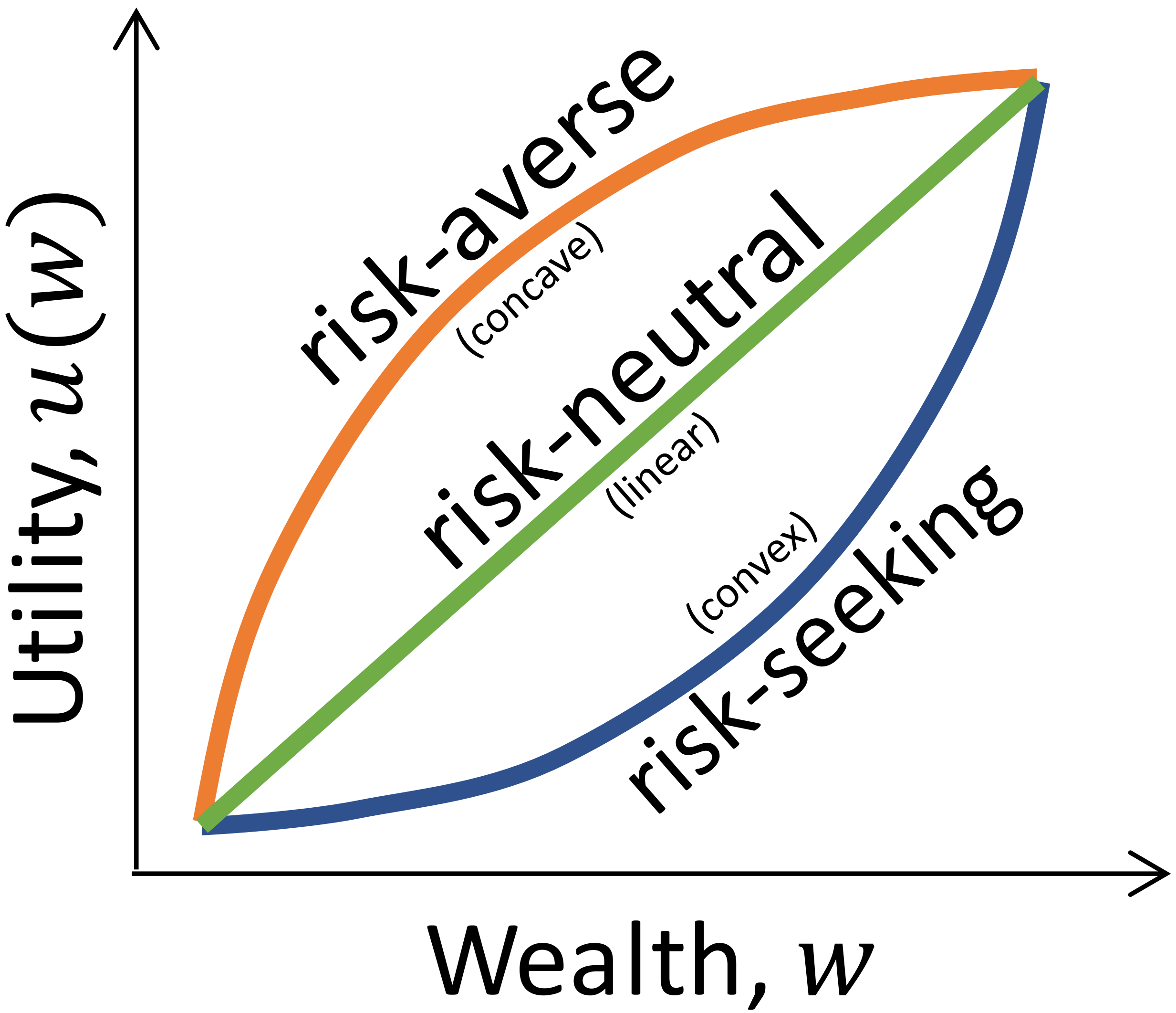
Exponential Utility Function:

$$u(w) = \begin{cases} e^{-\frac{w}{\rho}}, & \rho < 0 \\ -e^{-\frac{w}{\rho}}, & \rho > 0 \\ w, & \rho \to \pm\infty \end{cases}$$

(ρ: risk tolerance)

- $\rho < 0$: risk-seeking
- $\rho > 0$: risk-averse
- $\rho \to \pm\infty$: risk-neutral

Expected monetary value maximization is a special case of expected utility maximization.



Risk Neutrality

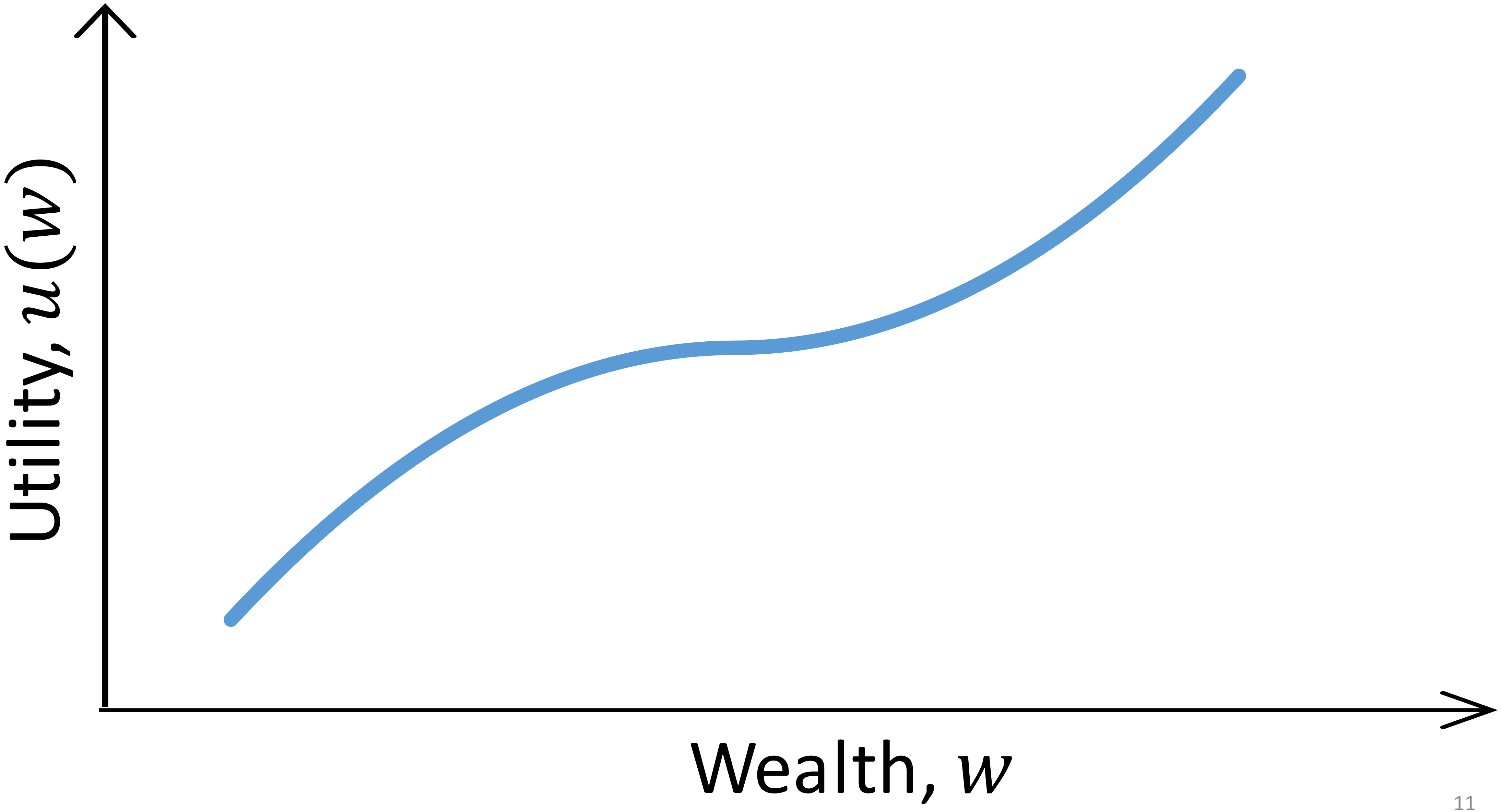
⬇

Linear Utility Function

⬇

Expected Utility Maximization
=
Expected Monetary Value Maximization

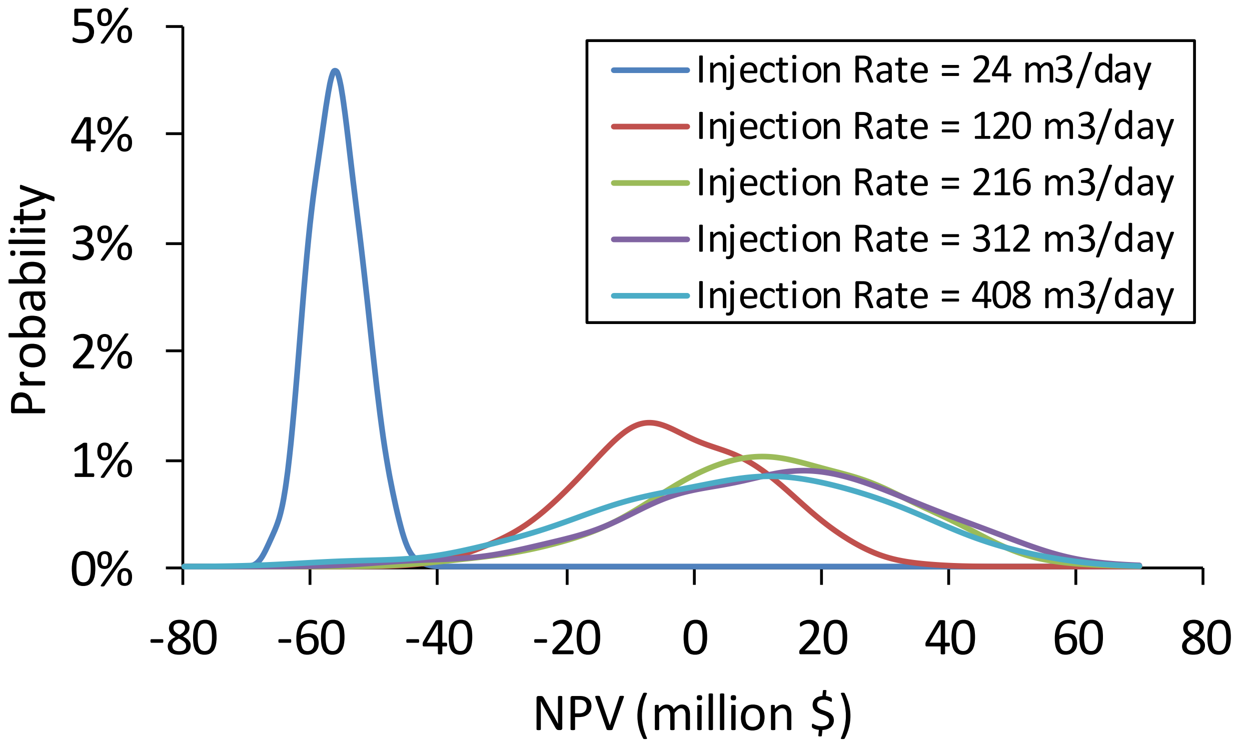
A person can have mixed risk attitudes.

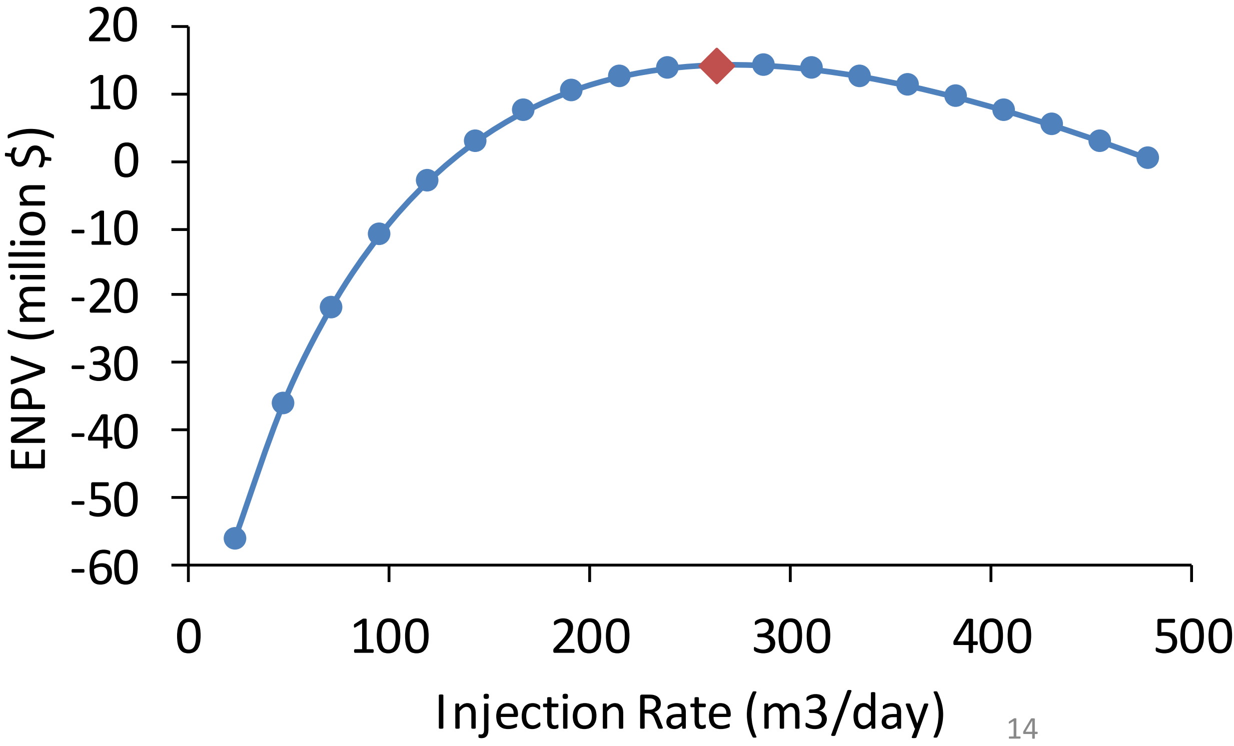


Impact of Risk Attitude on Reservoir Management Decisions in Long Term

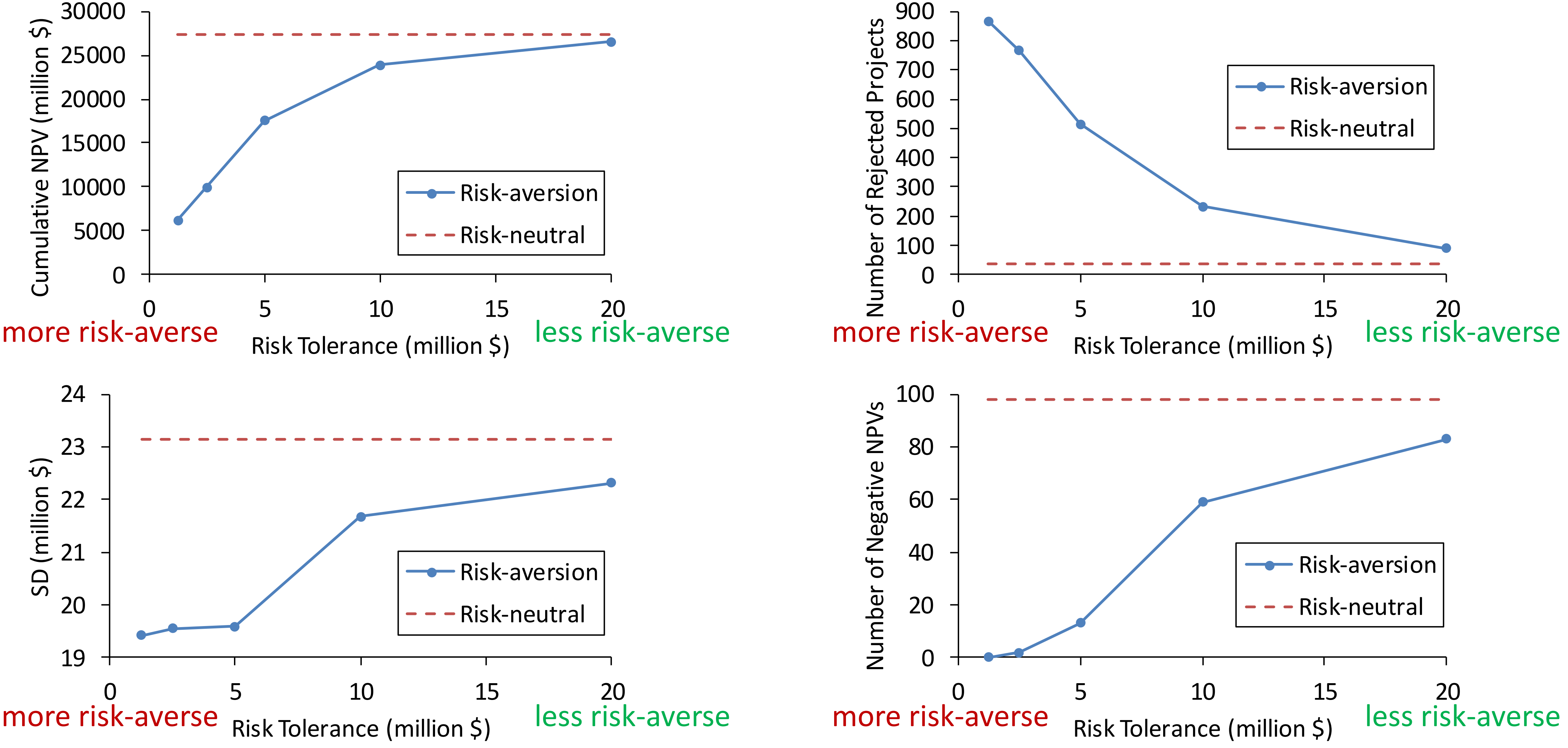
Modeling of Many Reservoir Management Projects

- Decline curve-based production model with 1 injector and 4 producers.
- Simulate 1,000 projects and 500 realizations for each project.
- Draw 1 realization randomly as the truth for each project.
- Optimize the injection rate over a life cycle of 5400 days (15 years) for each project.
- Use the exponential utility function.



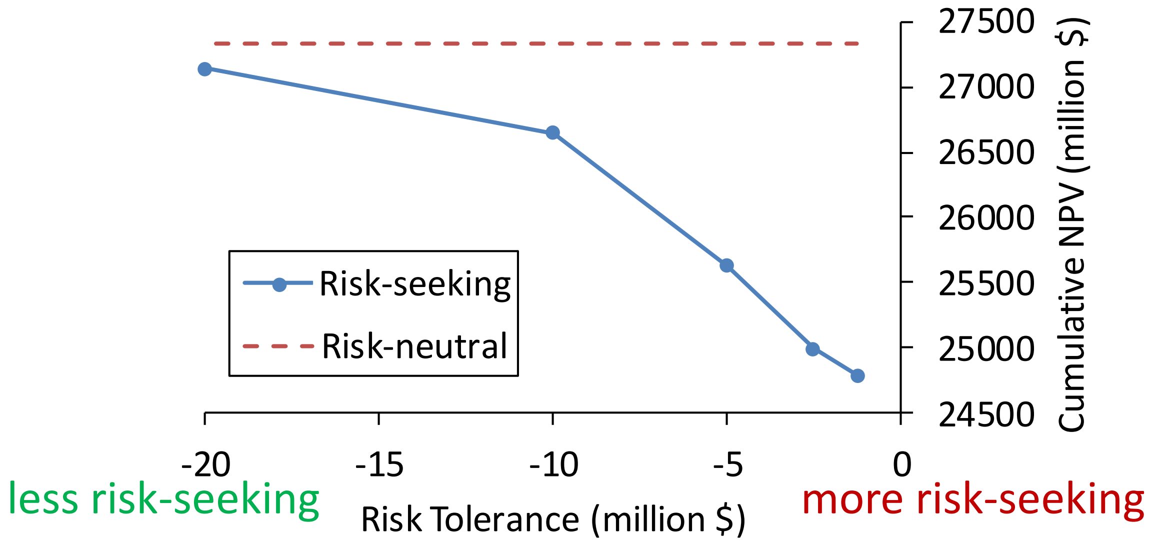


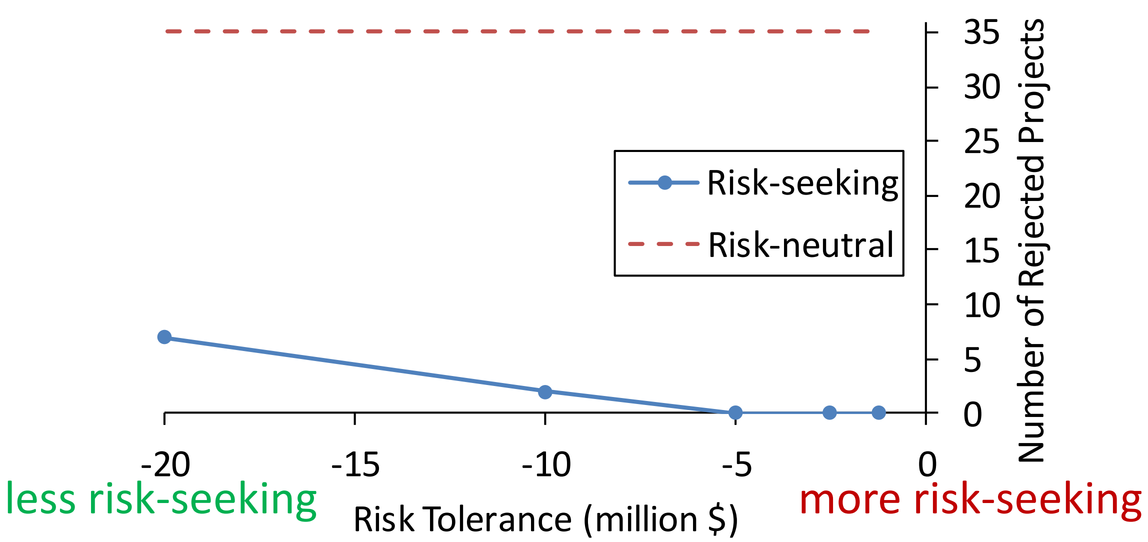
Impact of risk-aversion: Cumulative NPV is reduced.

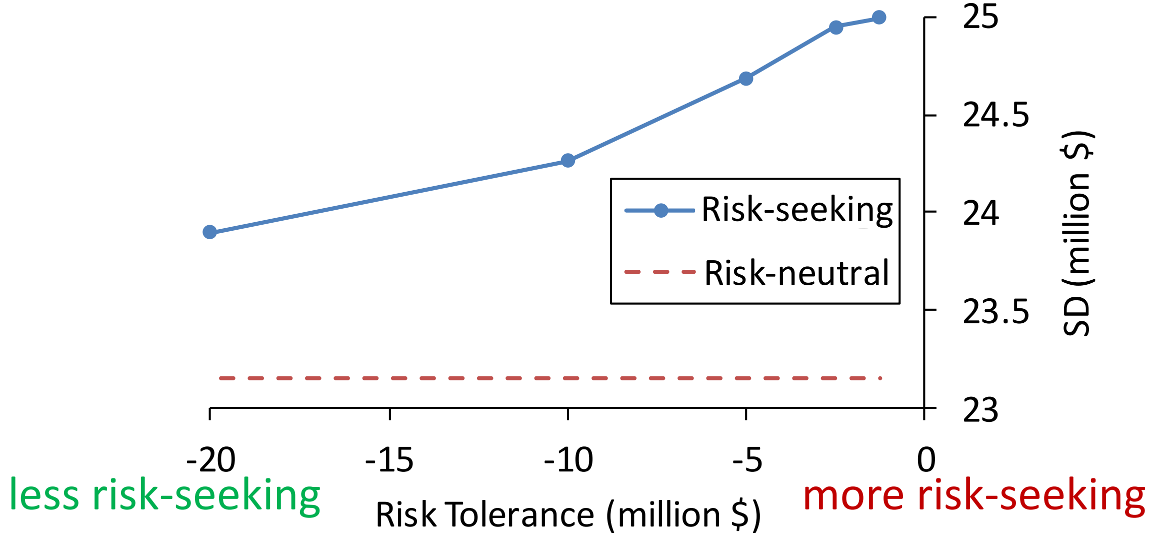


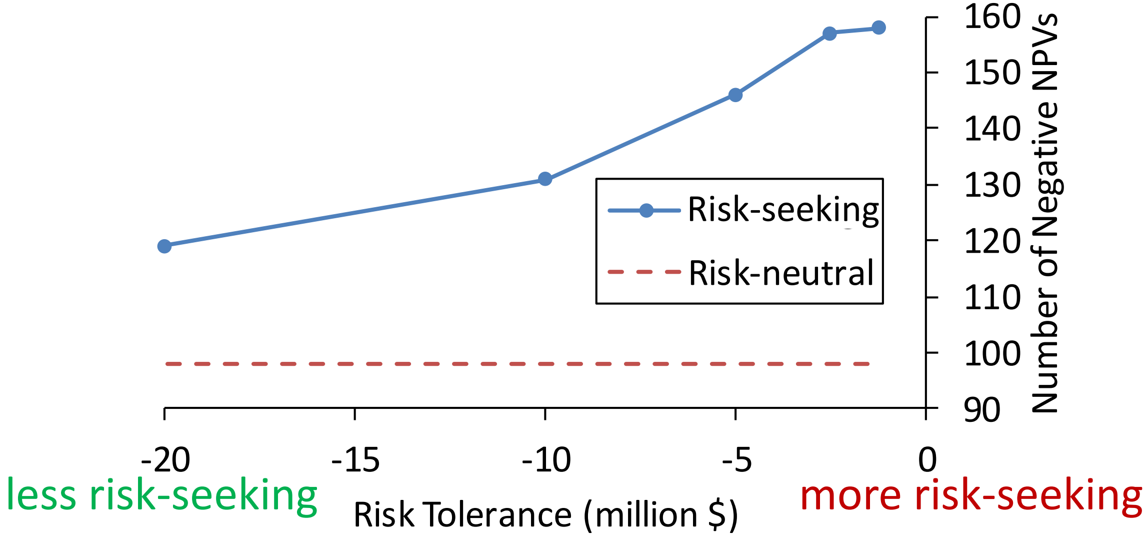
(Hong and Bratvold. Impact of Risk Attitude on Reservoir Management Decisions. Unpublished manuscript. Distribution of the results without the authors' authorization is not allowed.)

Impact of risk-seeking: Cumulative NPV is reduced.









(Hong and Bratvold. Impact of Risk Attitude on Reservoir Management Decisions. Unpublished manuscript. Distribution of the results without the authors' authorization is not allowed.)

Being risk-neutral maximizes the cumulative NPV.

	Cum. NPV	Rejected Projects	Negative Realized NPVs	SD of Realized NPVs
Risk-Averse	↓	↑	↓	↓
Risk-Neutral	max	-	-	-
Risk-Seeking	↓	↓	↑	↑

- Being risk-neutral maximizes the cumulative (or long-term) NPV.
- Being risk-averse reduces the cumulative NPV but leads to fewer negative realized NPVs and smaller standard deviation of realized NPVs.
- Being risk-seeking neither increases cumulative NPV nor reduces the number of negative realized NPVs and standard deviation of realized NPVs.
- Being relatively more risk-seeking from risk-averse toward risk-neutral can increase cumulative NPV.

Incorporating Risk Attitude in Ensemble-based Optimization

It is straightforward to perform expected utility maximization using any expected value optimizer.

	Alt 1	…	Alt N
Real 1	NPV_{11}	…	NPV_{1N}
…	…	…	…
Real M	NPV_{M1}	…	NPV_{MN}
EMV	$\boldsymbol{ENPV_1}$	**…**	$\boldsymbol{ENPV_N}$

⇨ Expected Value Optimizer ⇨ **Optimal Alternative with Max ENPV**

Utility Function
$u(NPV)$ ⇩

	Alt 1	…	Alt N
Real 1	$u(NPV_{11})$	…	$u(NPV_{1N})$
…	…	…	…
Real M	$u(NPV_{M1})$	…	$u(NPV_{MN})$
EU	$\boldsymbol{EU_1}$	**…**	$\boldsymbol{EU_N}$

⇨ Expected Value Optimizer ⇨ **Optimal Alternative with Max EU**

Mean-variance maximization can be replaced by expected utility maximization of exponential utility function.

Max
$\bar{w} - c\sigma_w^2$

$\Longleftrightarrow$

$\rho = \frac{1}{2C}$

Max
$\mathbb{E}[u(w)]$

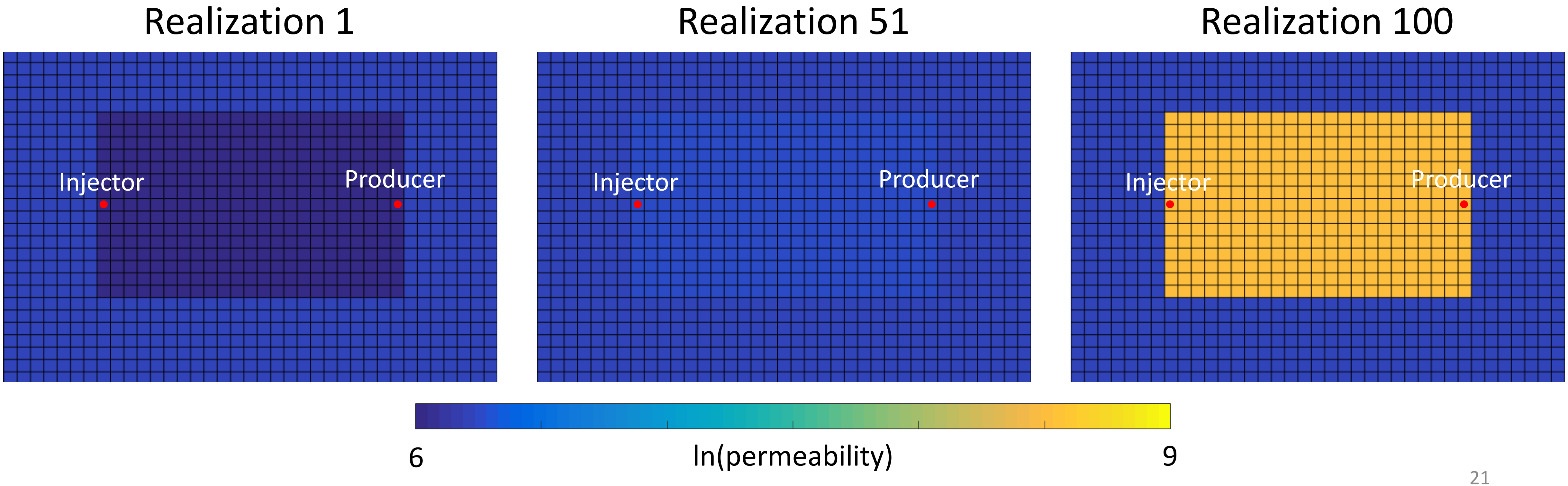
$$u(w) = \begin{cases} e^{-\frac{w}{\rho}}, & \rho < 0 \\ -e^{-\frac{w}{\rho}}, & \rho > 0 \\ w, & \rho \to \pm\infty \end{cases}$$

Advantages of using EU maximization:

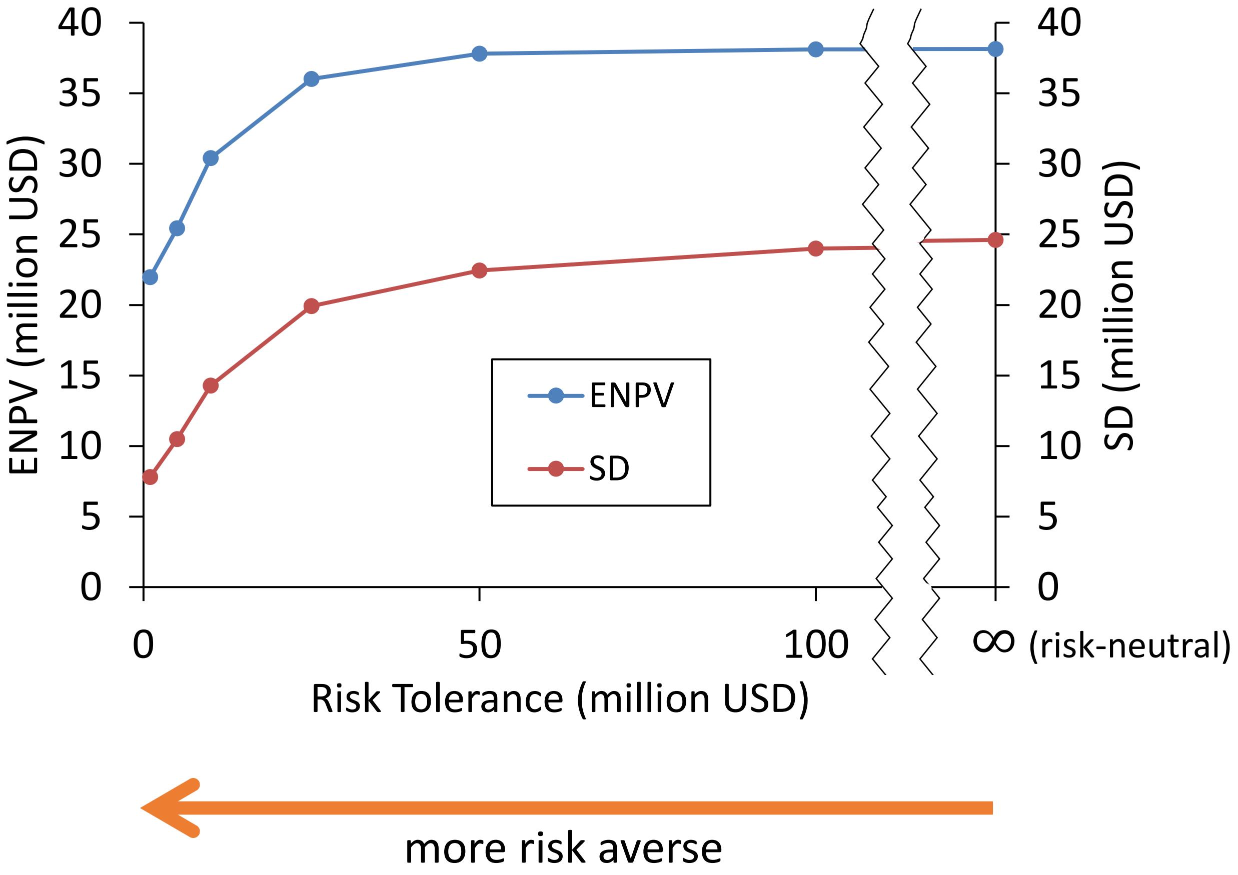
- Mean-variance maximization can be inconsistent for non-normal distributions. EU maximization is consistent for any distributions.
- No need to calculate variance during optimization: EU maximization suits any EV optimizer (e.g., EnOpt).

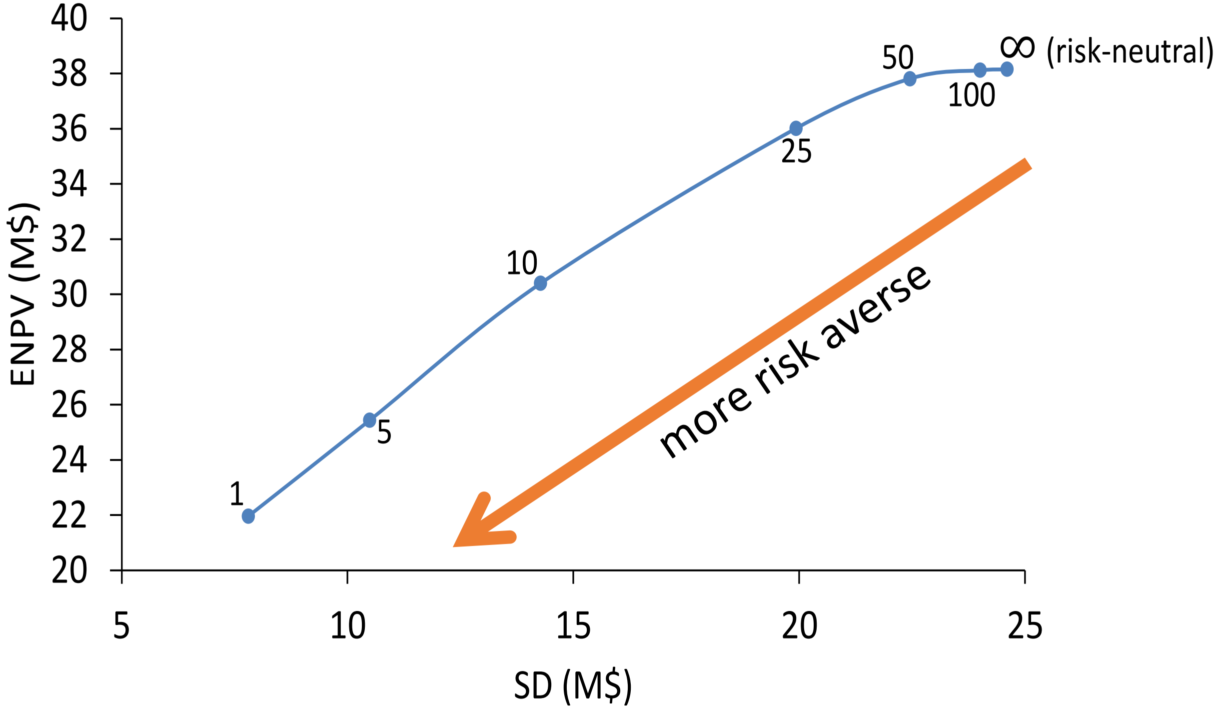
Example with Reservoir Simulation Model

- 2D model with 100 realizations.
- Monetary value measure is NPV.
- Exponential utility function is used for different risk tolerances.
- Optimize the injection rates over a life cycle of 60 months (60 control variables).
- EnOpt is used for EU maximization.



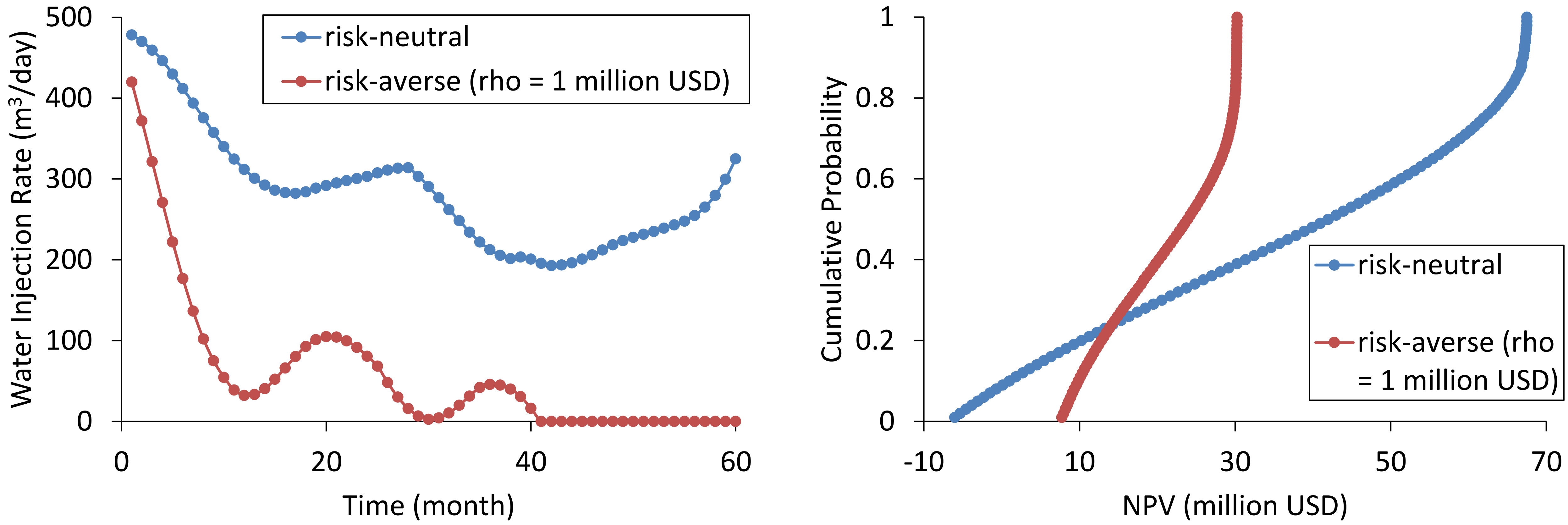
Sensitivity Analysis of Risk Aversion





(Hong and Bratvold. Using Expected Utility Theory to Enhance the Ensemble-based Optimization (EnOpt) for Incorporating Risk Attitude in Reservoir Management Decisions. Unpublished manuscript. Distribution of the results without the authors' authorization is not allowed.)

Sensitivity Analysis of Risk Aversion



(Hong and Bratvold. Using Expected Utility Theory to Enhance the Ensemble-based Optimization (EnOpt) for Incorporating Risk Attitude in Reservoir Management Decisions. Unpublished manuscript. Distribution of the results without the authors' authorization is not allowed.)

Take-Away Messages

- The expected utility theory is the normative model for accounting for risk attitude in rational decision making.
- Impact of risk attitude on the long-term profit over many projects:
  - Being risk-neutral maximizes the long-term profit.
  - Being risk-averse reduces the variance of realized project profits.
- The mean-variance maximization can be replaced by the expected utility maximization of an exponential utility function.
- Risk attitude can be easily accounted for in ensemble-based optimization when a utility function is used.
- Sensitivity analysis of risk attitude provides useful insight to support decision making under uncertainty.

Fit-for-purpose forecasting in Equinor

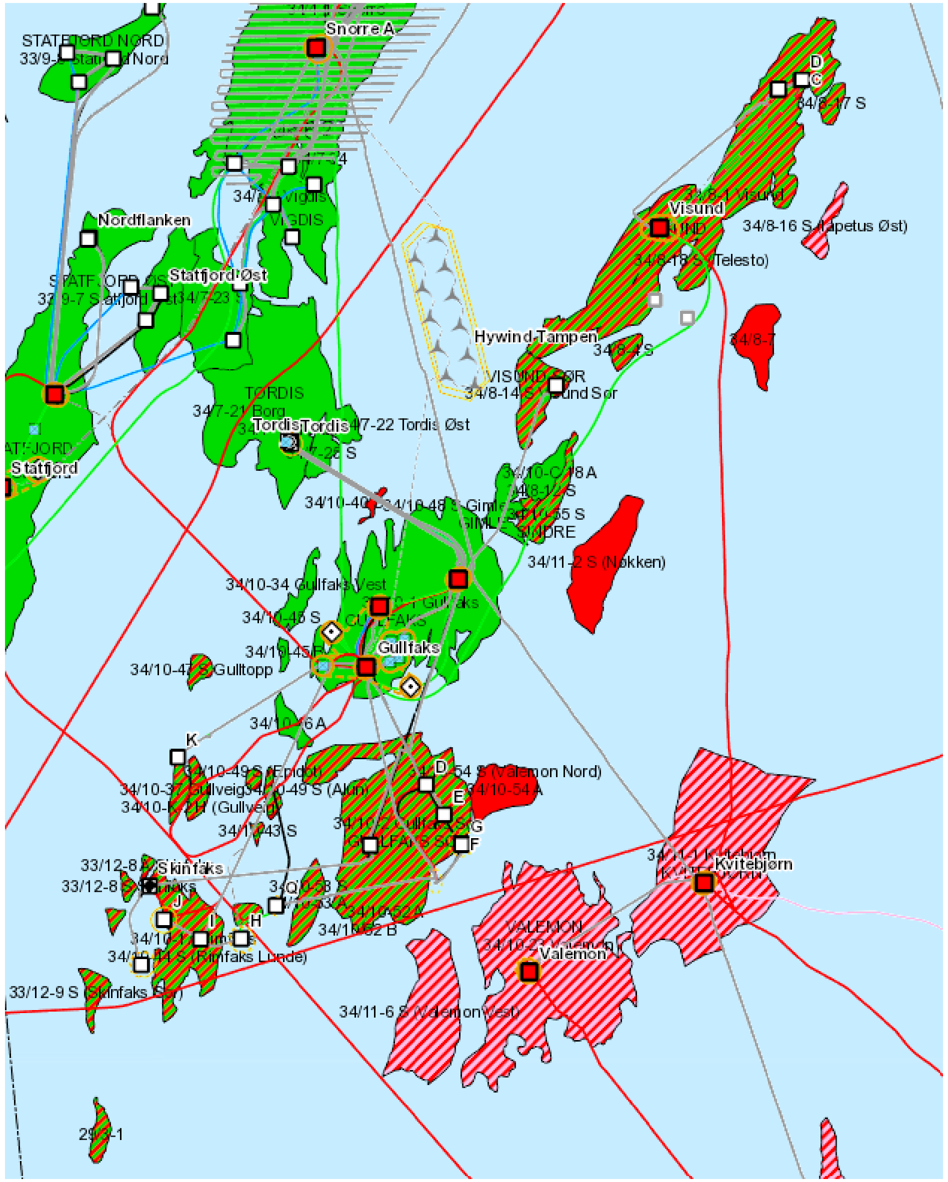
National IOR Center Workshop on
Production optimization, value of information and decision-making
2021-09-07

Outline

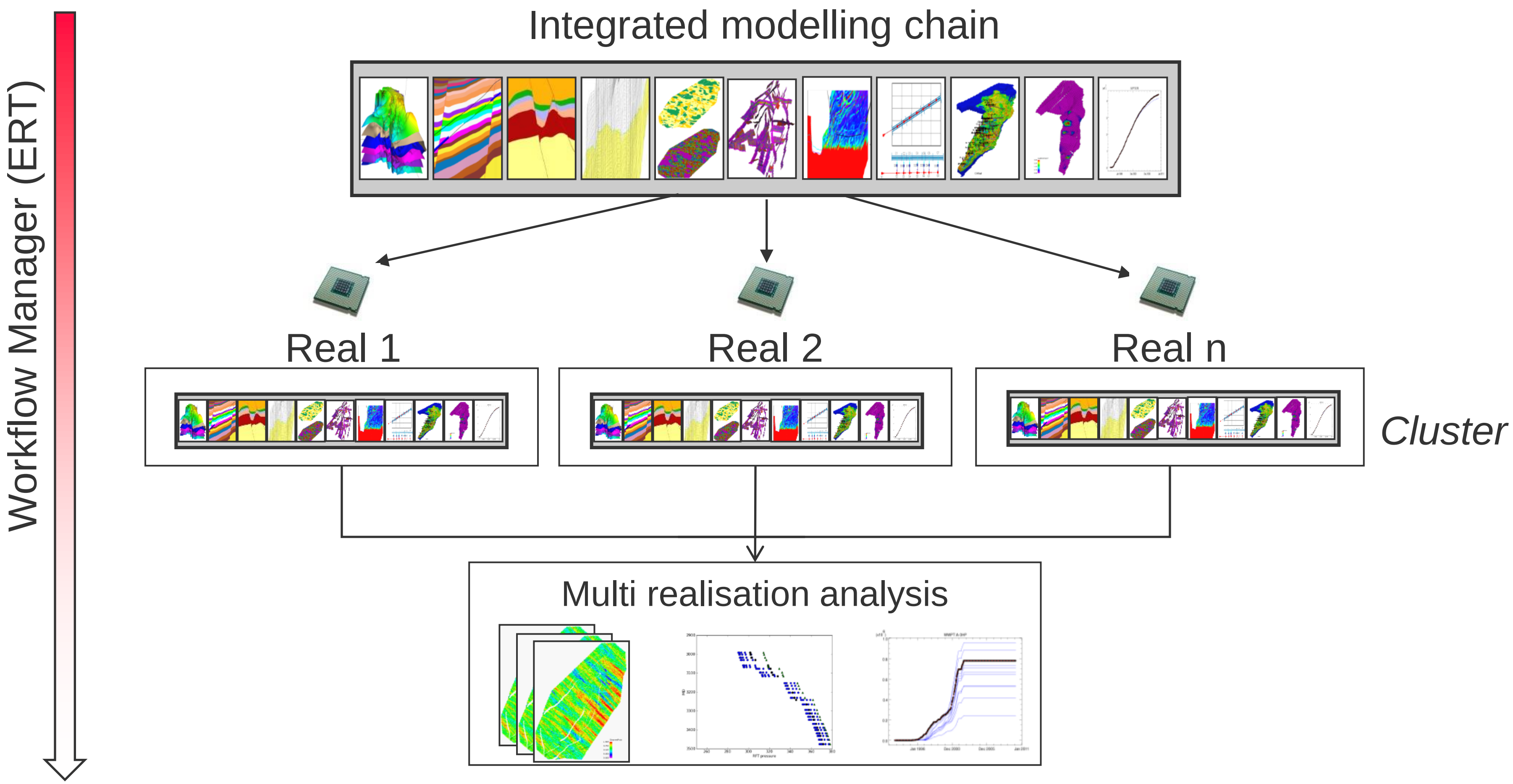
- Different purposes
- The forecasting toolbox
  - Multi-realisation reservoir modelling & FMU
  - Alternatives & challenges

Different forecasting purposes | Decision support for NCS oil & gas projects through the energy transition

- **Area development**
  - Handling a large portolio of decisions, from exploration to cessation
  - CO2 emission & «net zero» strategies
  - Lifetime extensions & infrastructure consolidation
- **Field development projects**
  - Typically smaller tie-back developments
- **Drainage strategy & IOR**
  - Infill drilling
  - Low pressure production
  - Gas blowdown otimization

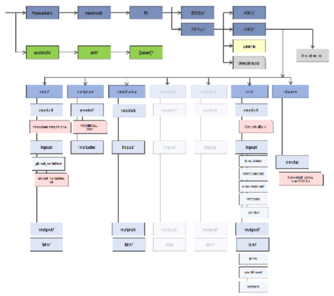


Multi-realization reservoir modelling & FMU | Automated workflow - running in parallel on a cluster



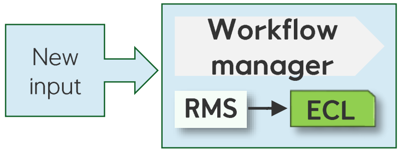
Multi-realization reservoir modelling & FMU | Different levels of implementation

- Start simple and then add value



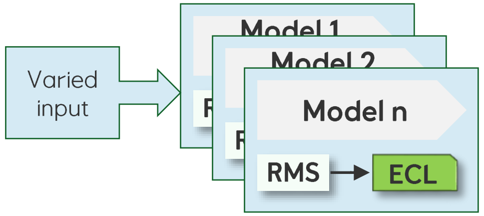
Recommended for all models

1. FMU standardisation (requirement for all new models)

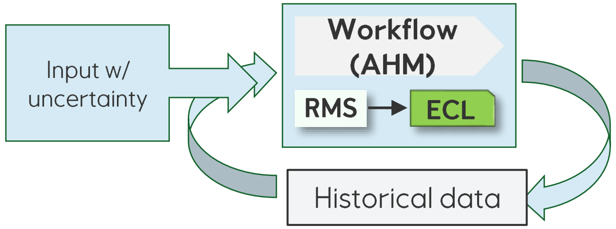


2. FMU workflow for fast model updates

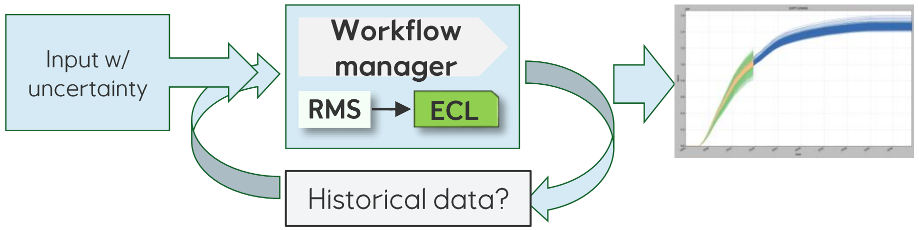
3. FMU workflow for sensitivities



4. Big loop Assisted History Matching (AHM) (when dynamic data/observations are available)



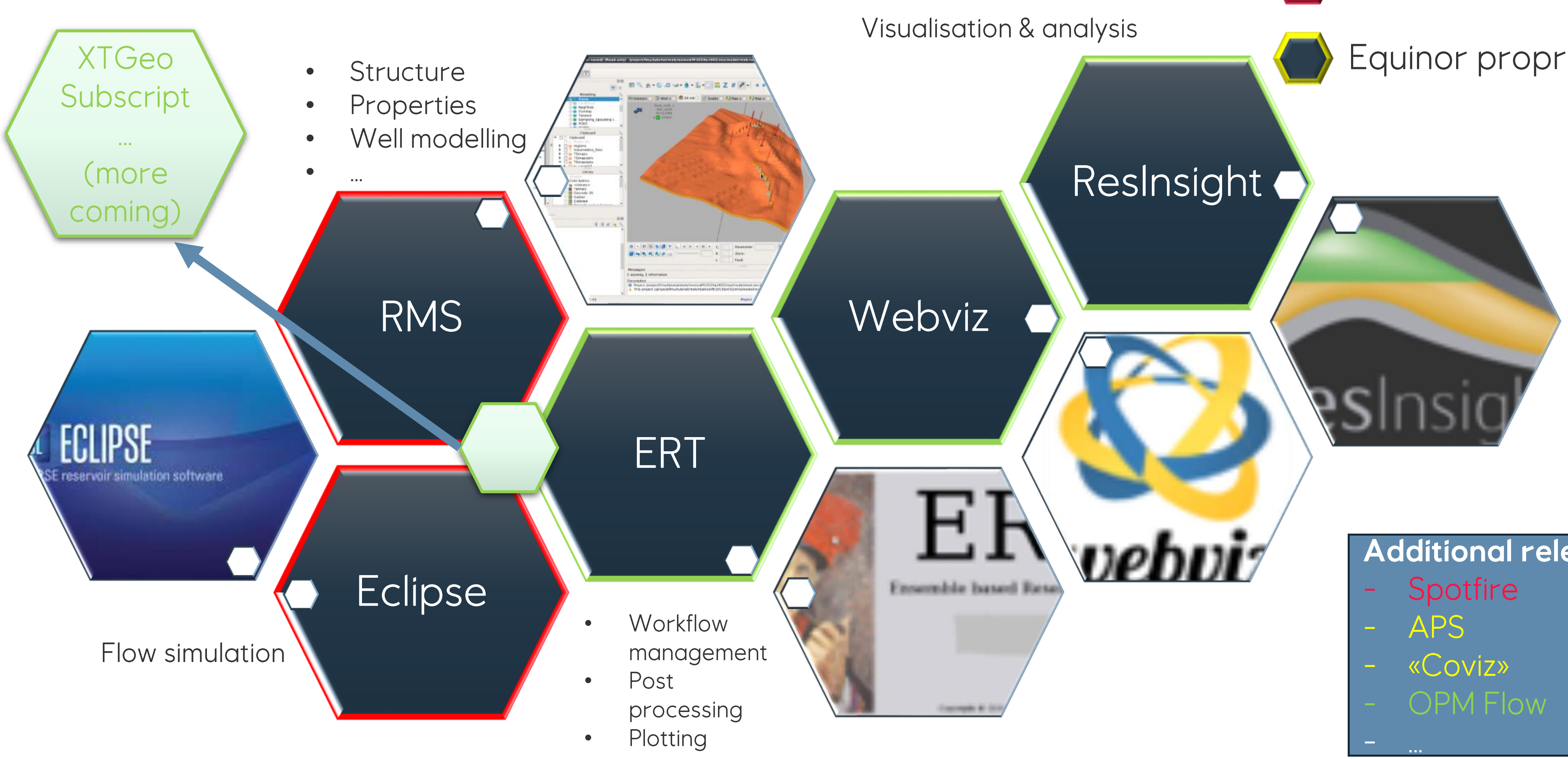
5. Ensemble based approach capturing uncertainty in predictions



Open

Components of FMU

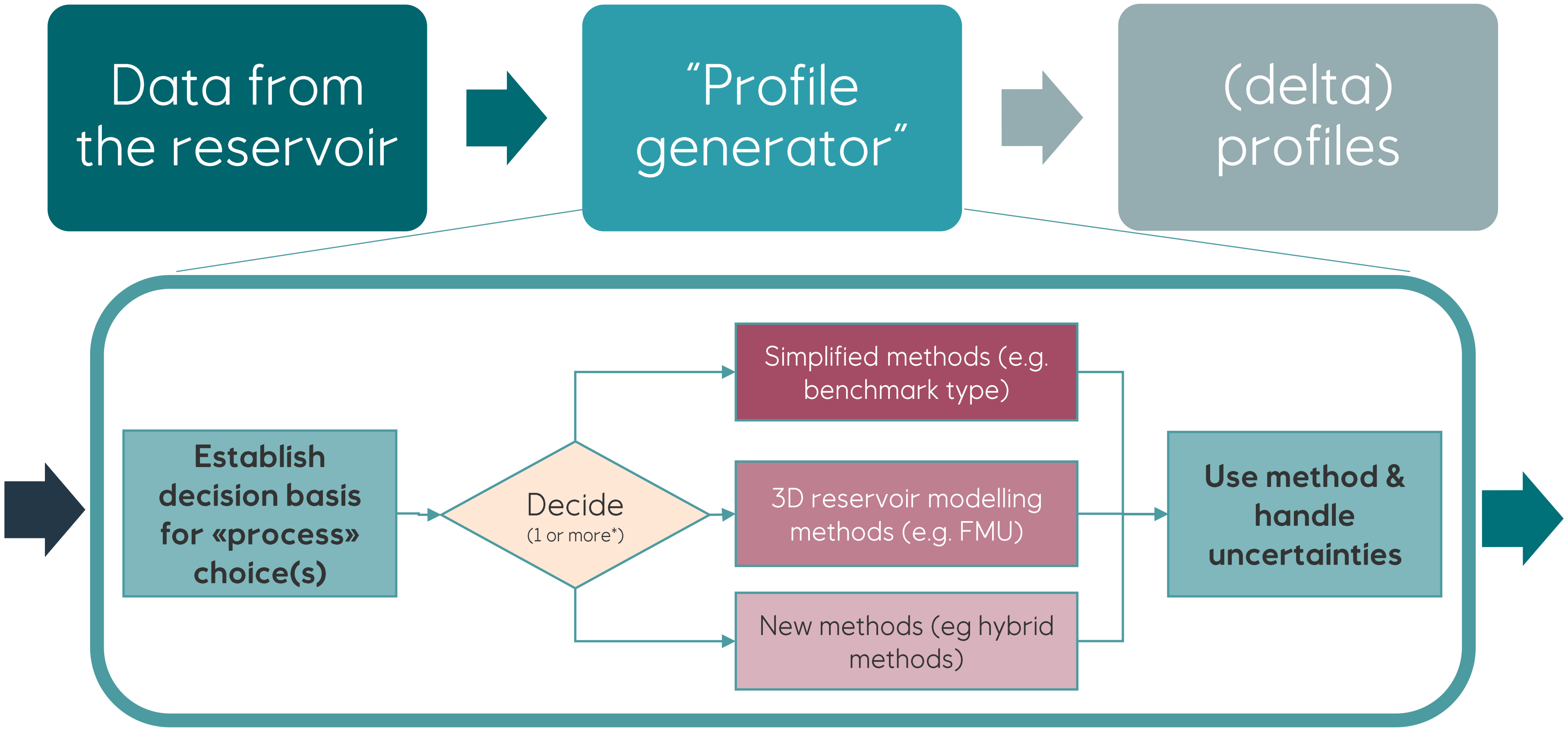
- Open source software
- Commercial software
- Equinor proprietary



Additional relevant tools:
- Spotfire
- APS
- «Coviz»
- OPM Flow
- ...

Open

Forecasting alternatives

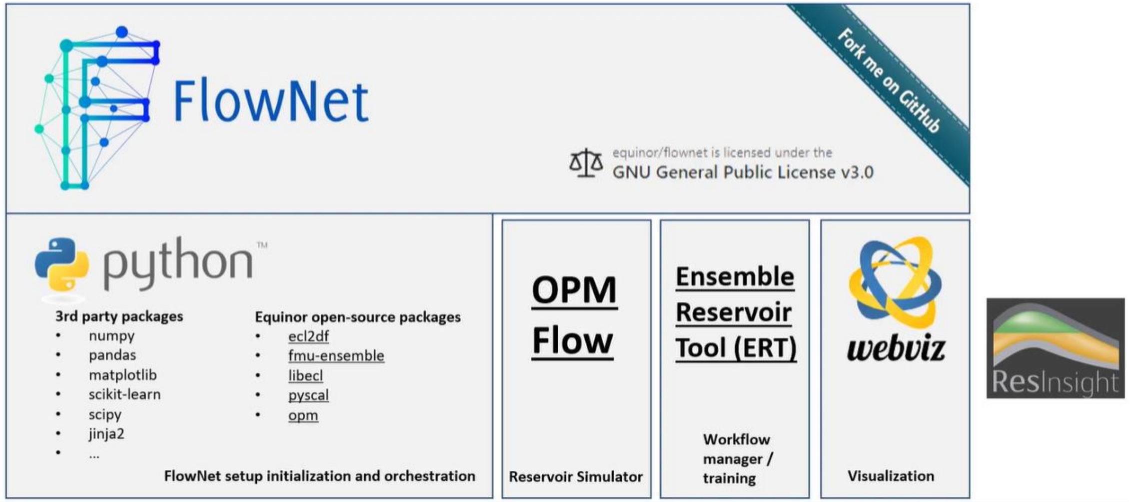


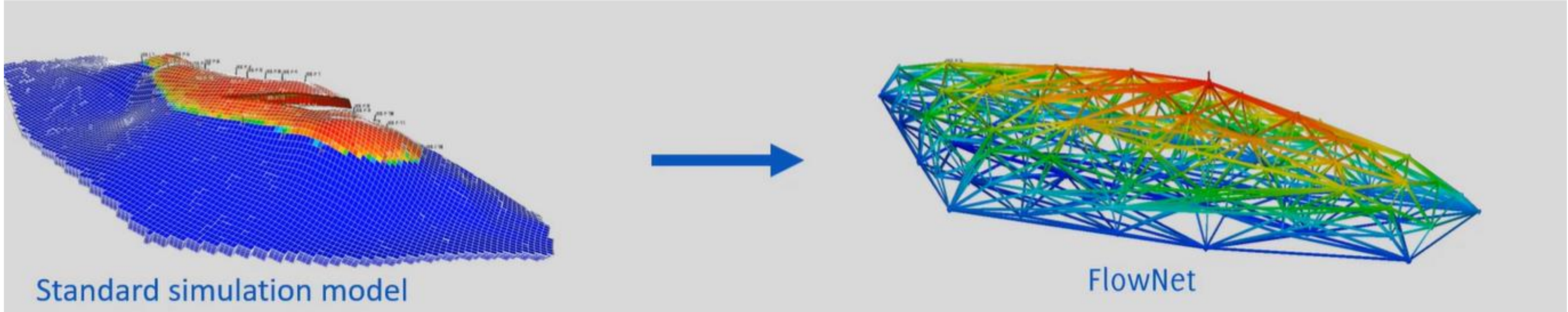
TNO innovation for life   equinor

Hybrid method under development | FlowNet

Fully open-source software stack

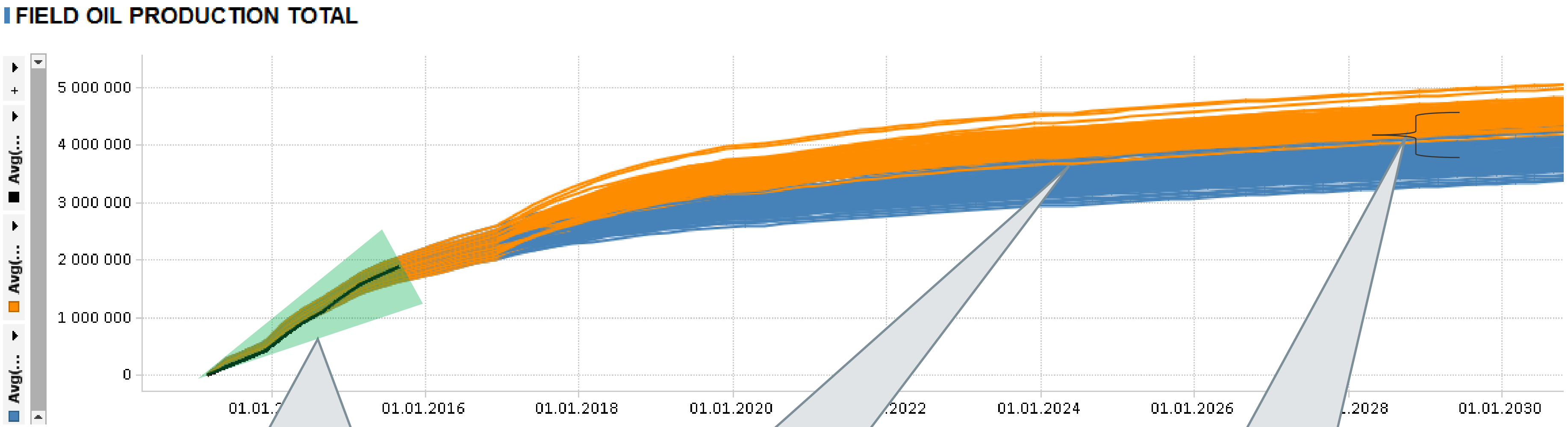
- **combines** elements of other flow network models
  - 3D-network of nodes with 1D-flow paths connecting them
- **inherits complex functionalities** from the used reservoir simulator
  - multiphase behaviour, well behaviour, etc, etc…
- can build models directly from existing **simulation models** (implemented) or **directly from other data sources** (to be implemented)
- trains an ensemble of models using **ES-MDA**
- is **free to use** and **open-source**: a **collaborative** effort





A. Kiærr, O.P. Lødøen, W. De Bruin, E. Barros and O. Leeuwenburgh, Conference Proceedings, ECMOR XVII, Sep 2020, Volume 2020, p.1 - 18

Fit-for-purpose forecasting challenges | Uncertainties & parameterization



HM parametrization: often just fit for AHM

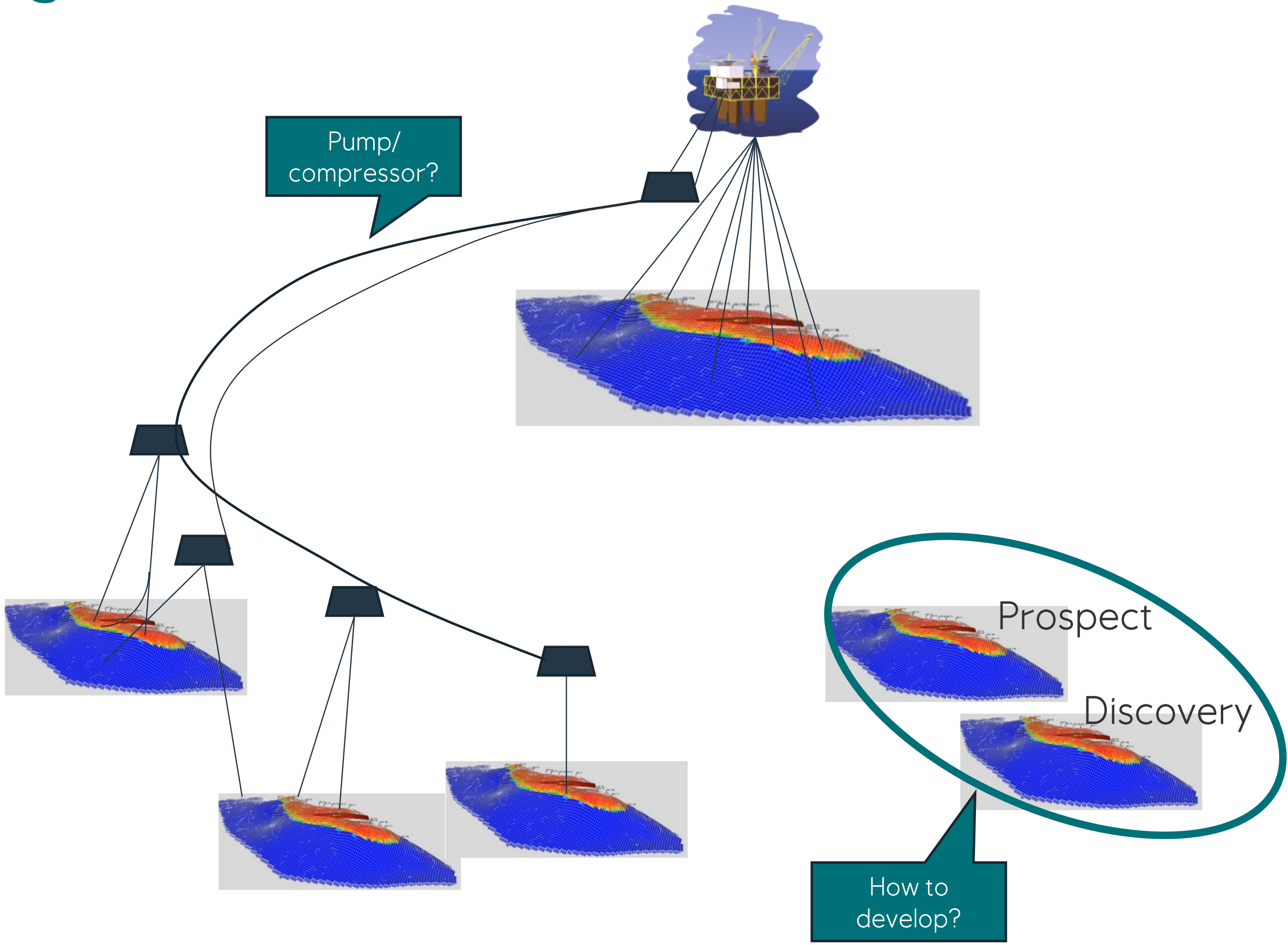
Parametrization to capture uncertainty for *full field forecast* : need to add uncertainties – typically on prediction set-up, but often from t_0

Parametrization to capture uncertainty in *delta production*: Often different than for full field forecast equinor

Fit-for-purpose forecasting challenges | Production networks & upsides

- Modelling of the production network needed for proper forecasting
  - Uncertainties in network model could have a major impact on forecasts and decisions

- Capturing possible production from prospect could be important for choosing the right field development concept



Summary

- Equinor´s main forecasting method is multi-realization reservoir modelling
  - A well-established technology that handles uncertainties
  - Sometimes challenging to finalize models in practice to provide fit-for-purpose forecasts

- Work ongoing to mature alternatives, including more data driven approaches

Fit-for-purpose forecasting in Equinor

Eivind Bakken, Sr Specialist Reservoir Technology – Technology, Digitalization & Innovation

National IOR Center Workshop on Production Optimization, Value of Information and Decision-Making
On-line, 7-8 September 2021

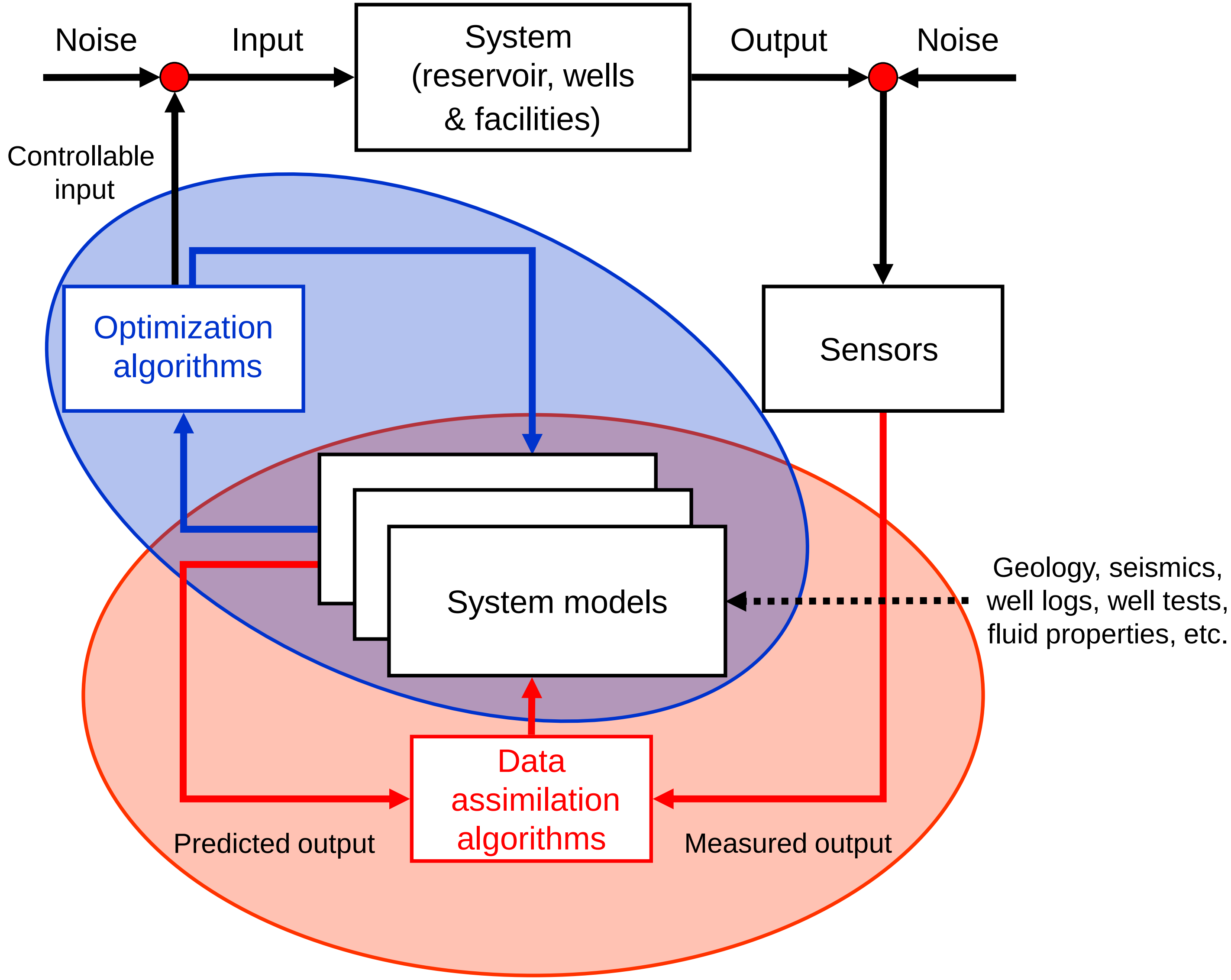
Historical developments in production optimization (from a reservoir-engineering perspective)

Jan Dirk Jansen
Delft University of Technology

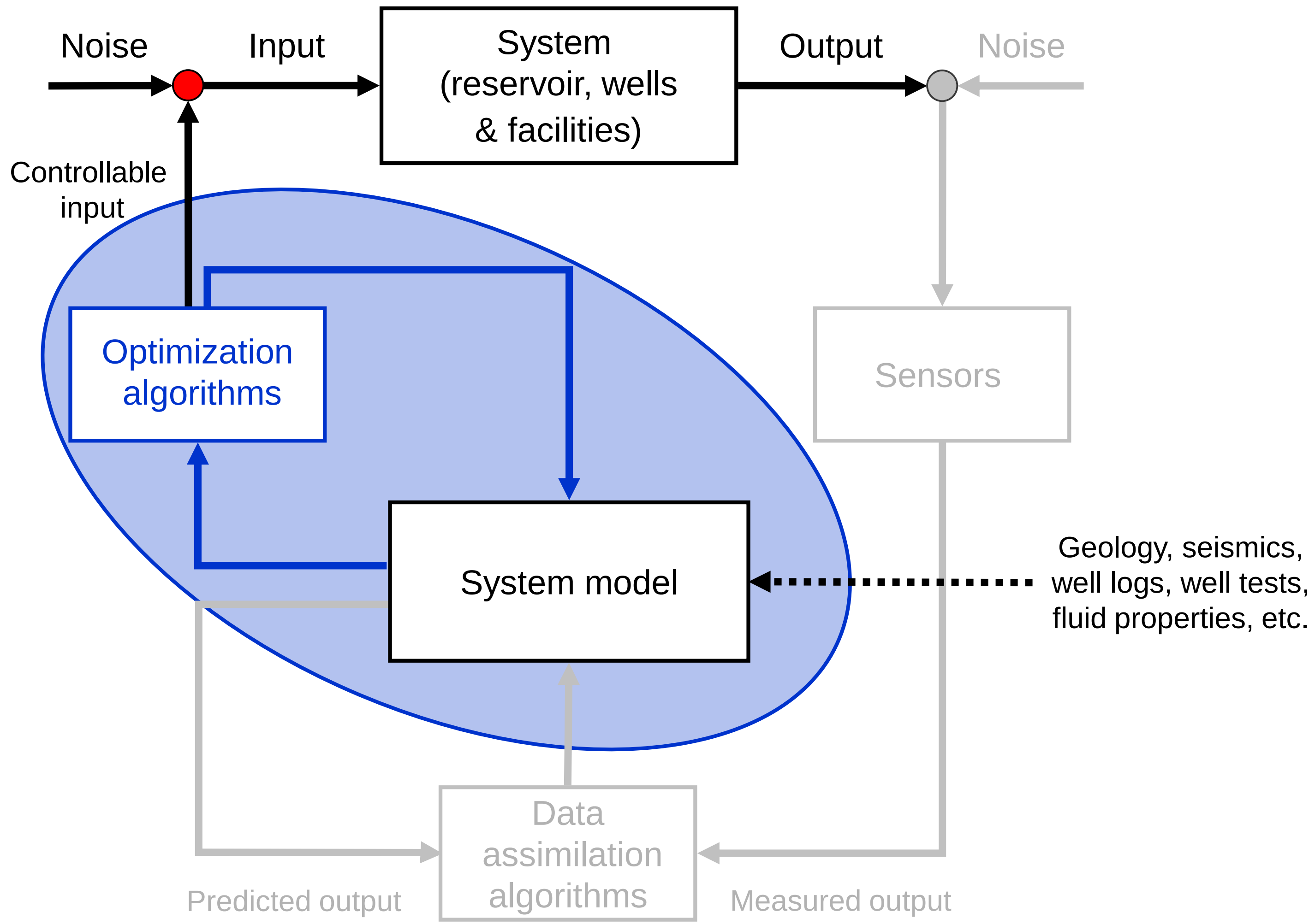
TU Delft

The National IOR Centre of Norway

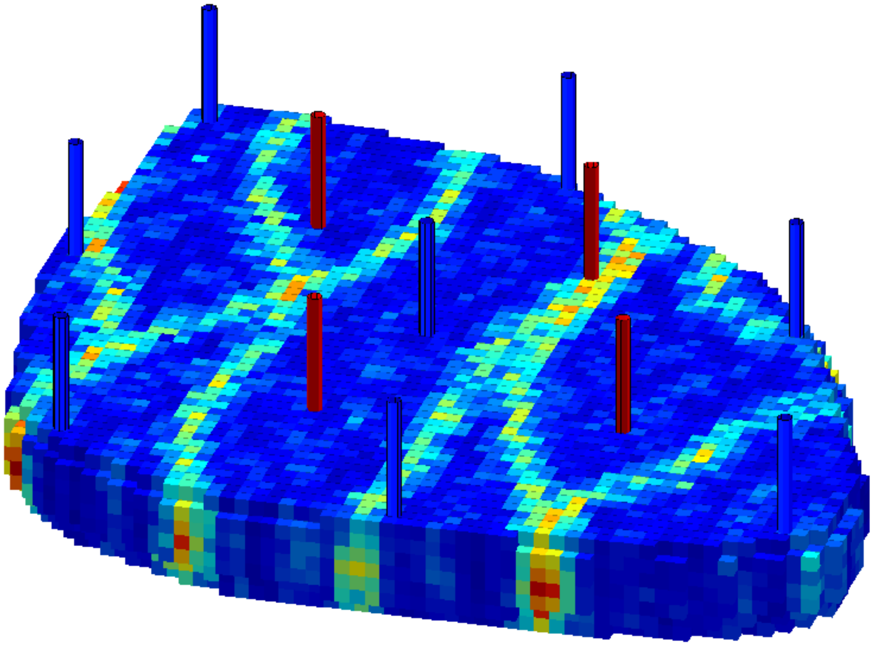
Closed-loop reservoir management



1) "Open-loop" flooding optimization



12-well example (1)

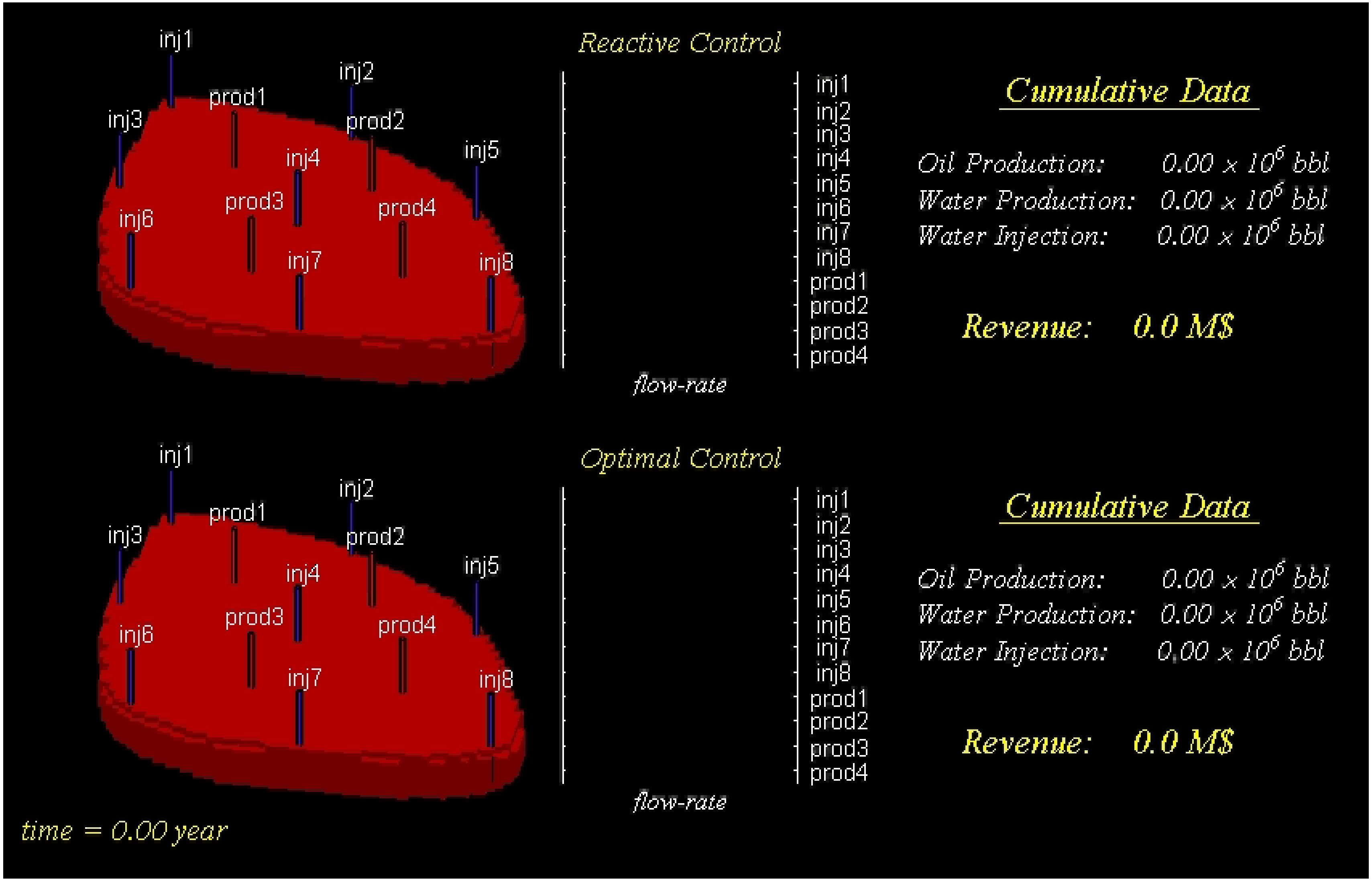


Van Essen et al., 2006

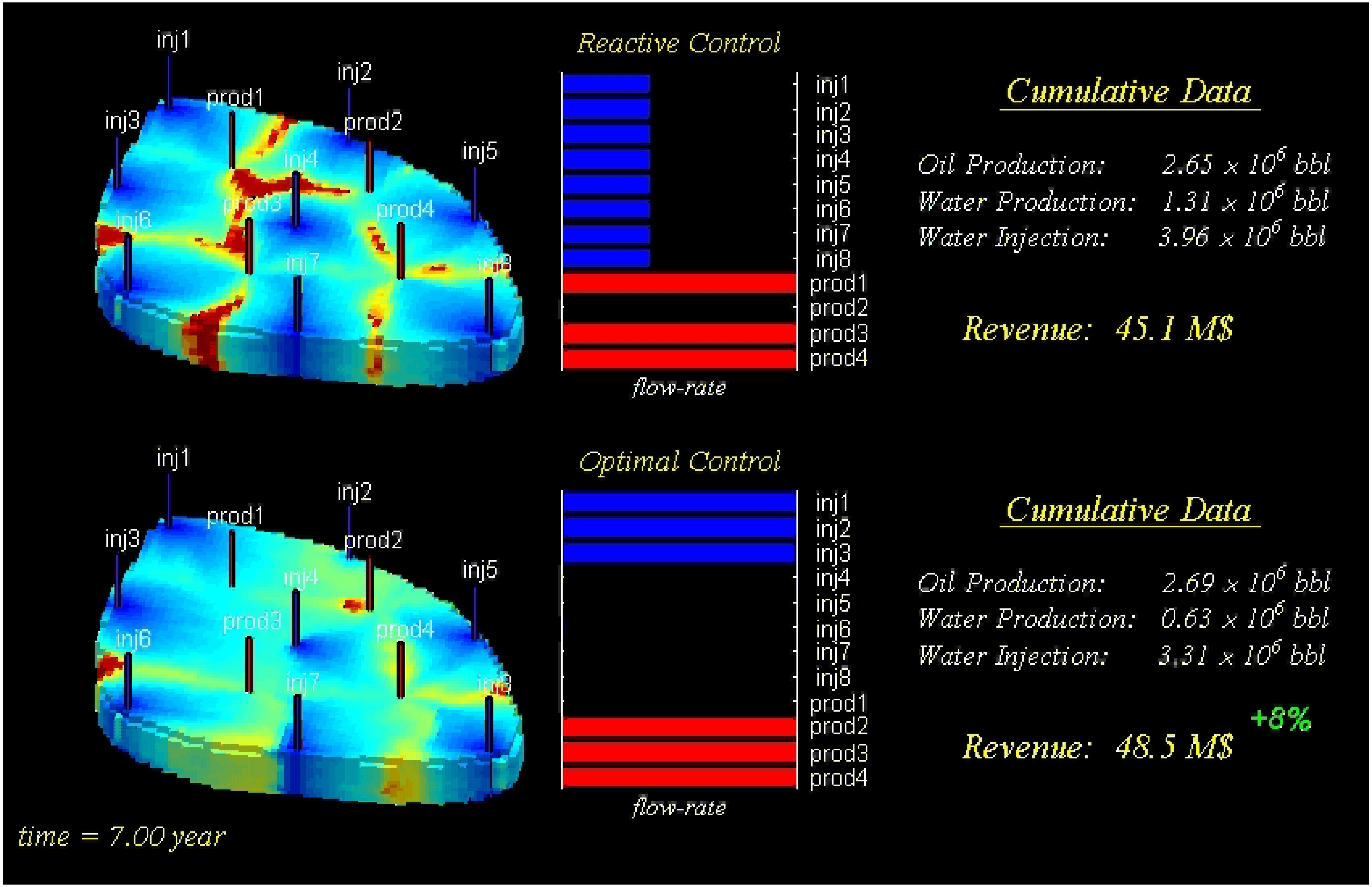
- 3D reservoir
- High-permeability channels
- 8 injectors, rate-controlled
- 4 producers, BHP-controlled
- Production period of 10 years
- 12 wells x 10 x 12 time steps

  => 1440 optimization parameters
- Bound constraints on controls
- Optimization of monetary value (oil revenues minus water costs)

12-well example (2)



12-well example (3)

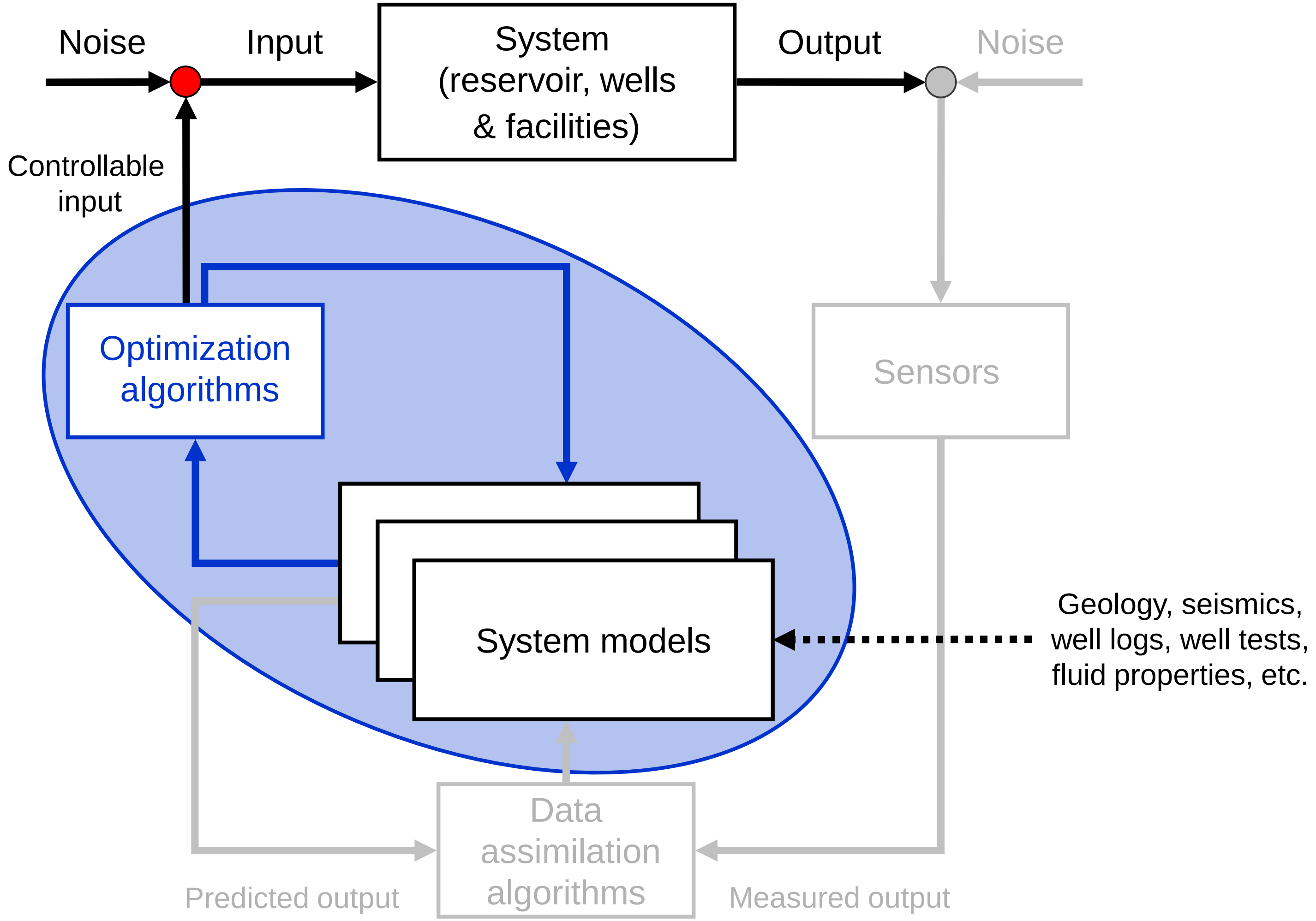


Why this wouldn’t work

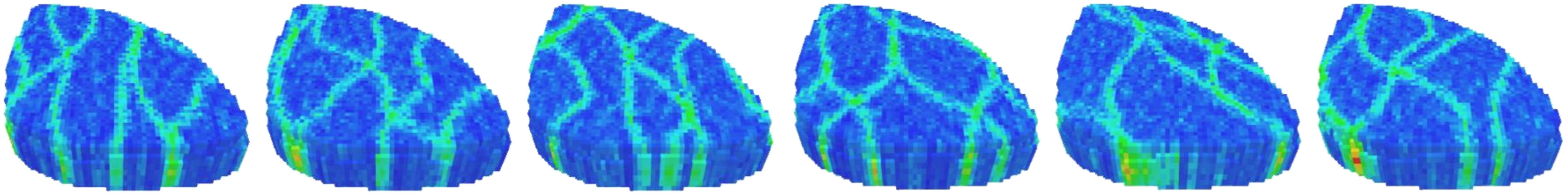
- Real wells are sparse and far apart
- Real wells have more complicated constraints
- Field management is usually production-focused
- Long-term optimization may jeopardize short-term profit
- Production engineers don’t trust reservoir models anyway

- We do not know the reservoir!

2) “Robust” open-loop flooding optimization



Robust optimization example



Van Essen et al., 2006

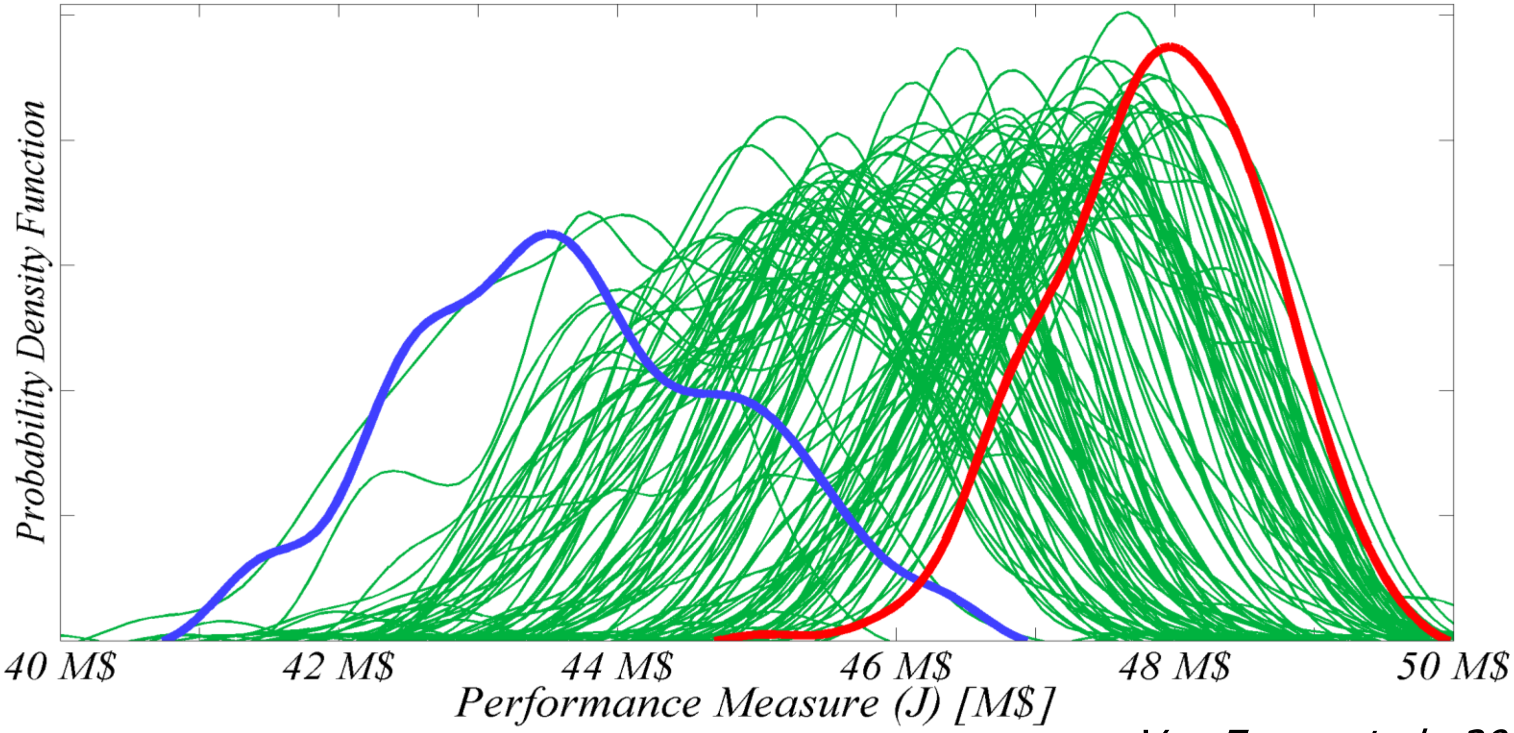
- 100 realizations
- Optimize expectation of objective function

$$\max_{\mathbf{u}_{1:K}} \frac{1}{N_r} \sum_{i=1}^{N_r} J^i \left(\mathbf{u}_{1:K}, \mathbf{m}_i \right)$$

Robust optimization results

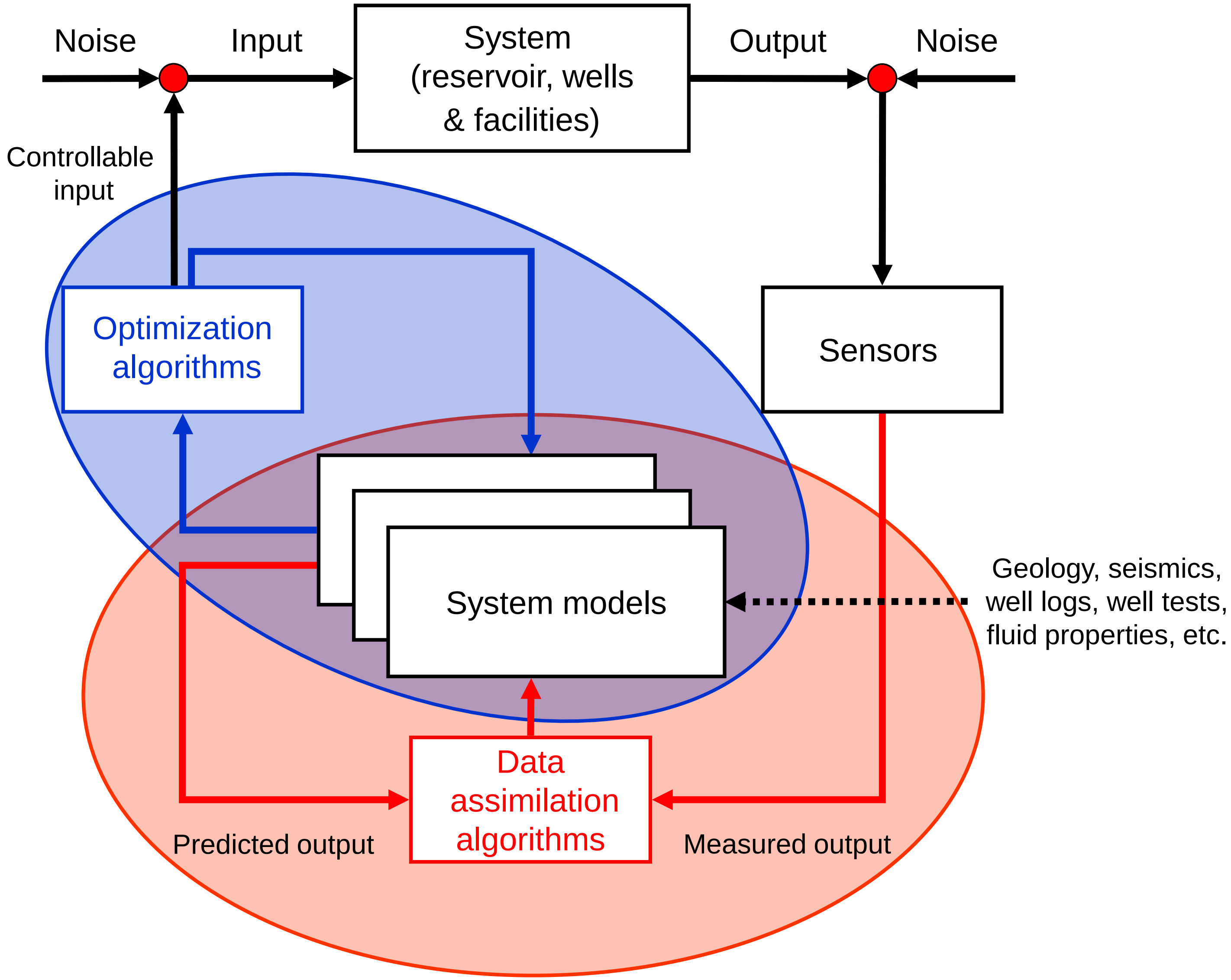
3 control strategies applied to set of 100 realizations:

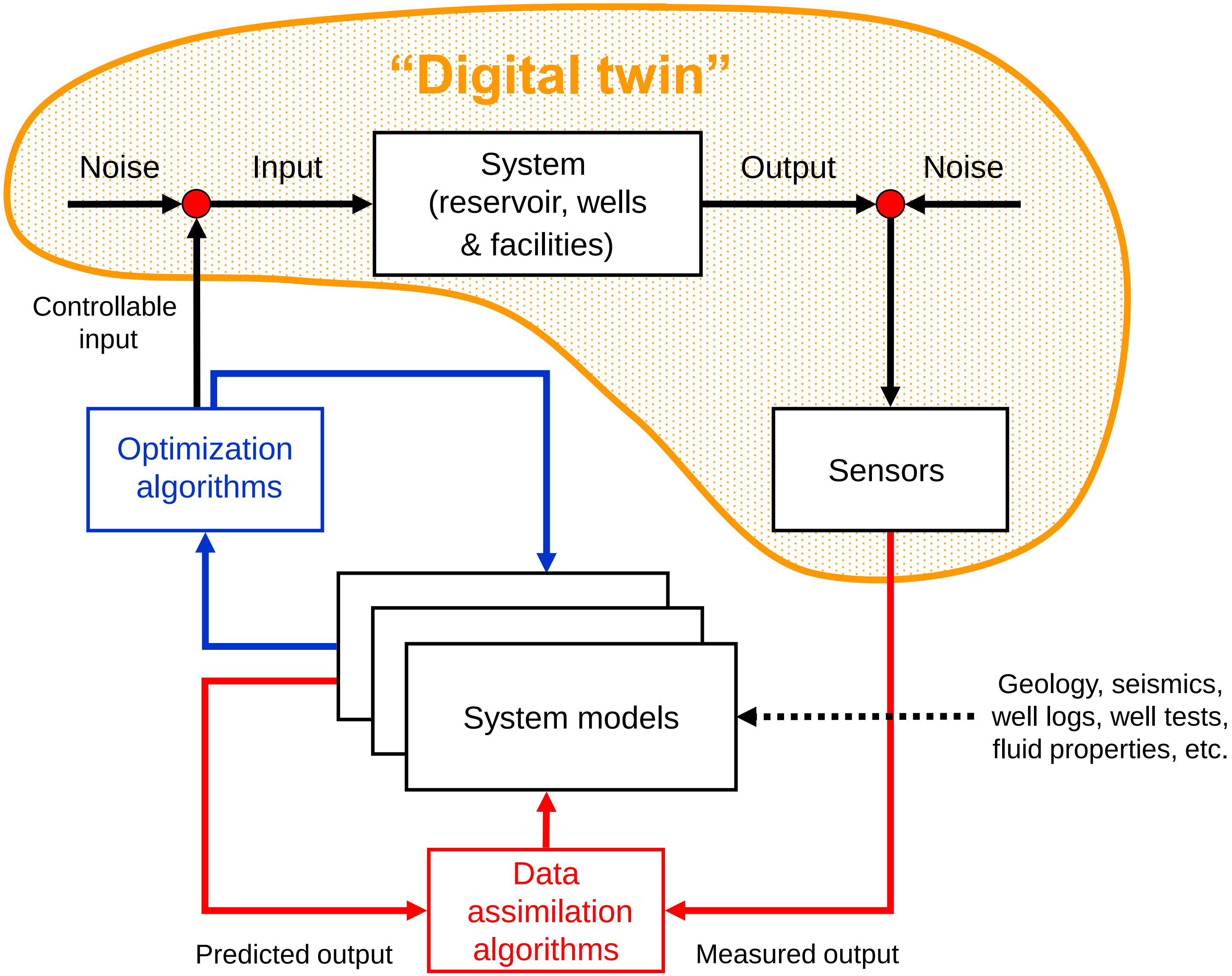
reactive control, nominal optimization, robust optimization



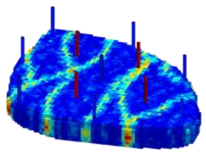
Van Essen et al., 2006

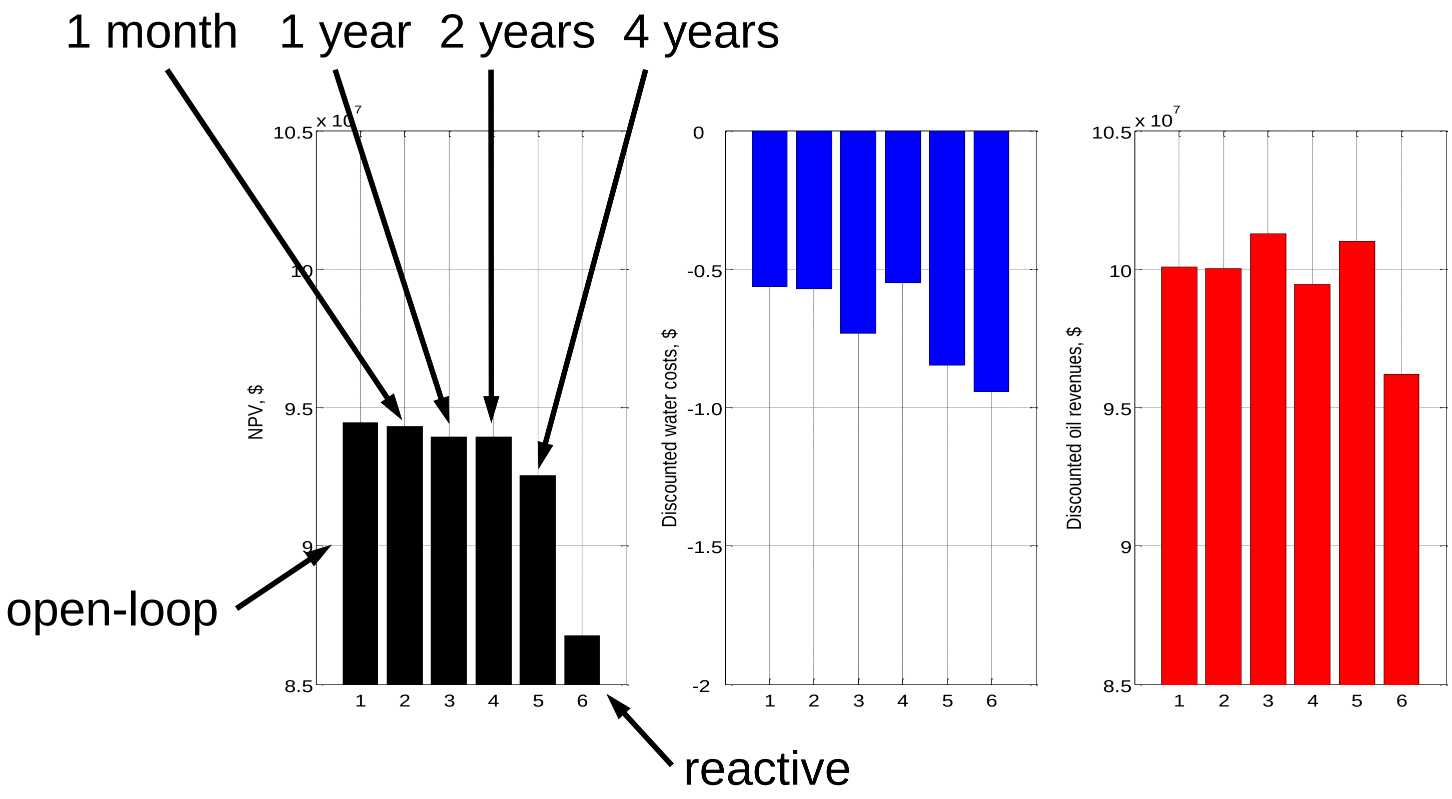
3) Closed-loop flooding optimization




"Digital twin"
Noise
Input
System
(reservoir, wells
& facilities)
Output
Noise
Controllable
input
Optimization
algorithms
Sensors
System models
Geology, seismics,
well logs, well tests,
fluid properties, etc.
Data
assimilation
algorithms
Predicted output
Measured output

Closed-loop optimization
NPV and contributions from water & oil production





Optimization techniques

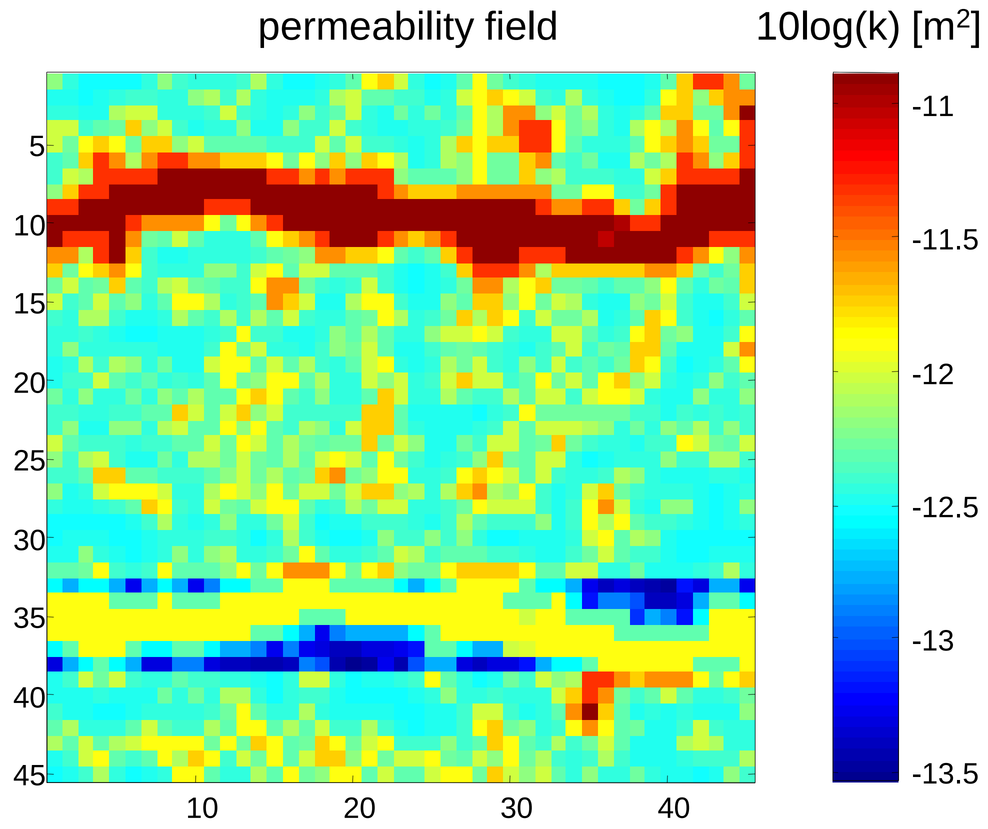
- Global versus local
- Gradient-based versus gradient-free
- Constrained versus non-constrained
- ‘Classical’ versus ‘non-classical’
  (simulated annealing, particle swarms, etc.)
- We use ‘optimal control theory’ or ‘adjoint-based’ optimization
- Has been proposed for history matching (Chen et al. 1974, Chavent et al. 1975, Li, Reynolds and Oliver 2003) and for flooding optimization (Ramirez 1987, Asheim 1988, Virnovski 1991, Zakirov et al. 1996, Sudaryanto and Yortsos, 2000, Brouwer and Jansen 2004, Sarma et al. 2004)

Optimal control theory, summary

- Gradient based optimization technique – local optimum
- Gradients of objective function with respect to controls obtained from ‘adjoint’ equation
- Gradients can be used with steepest ascent, quasi Newton, or trust-region methods
- Results in dynamic control strategy, i.e. controls change over time
- Computational effort independent of number of controls
- Output constraints not trivial; various techniques used
- Implementation is code-intrusive

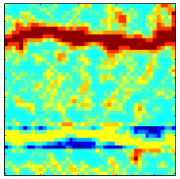
Classic example; smart horizontal wells

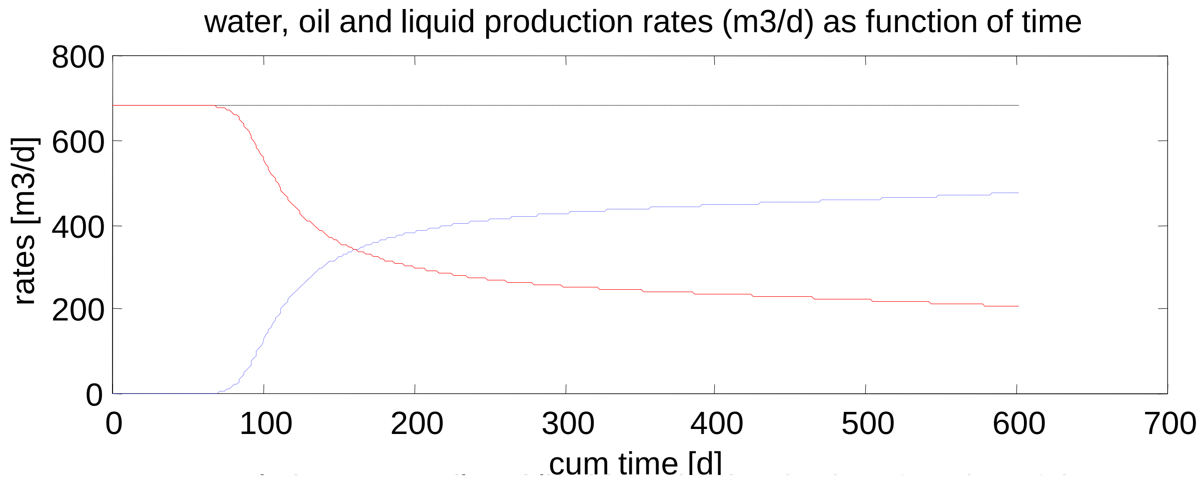
- 45 x 45 grid blocks
- 45 inj. & prod. segments
- p_{wf}, q_t at segments known
- 1 PV injected, $q_{inj} = q_{prod}$
- oil price r_o = 80 \$/m^3
- water costs r_w = 20 \$/m^3
- discount rate b = 0%

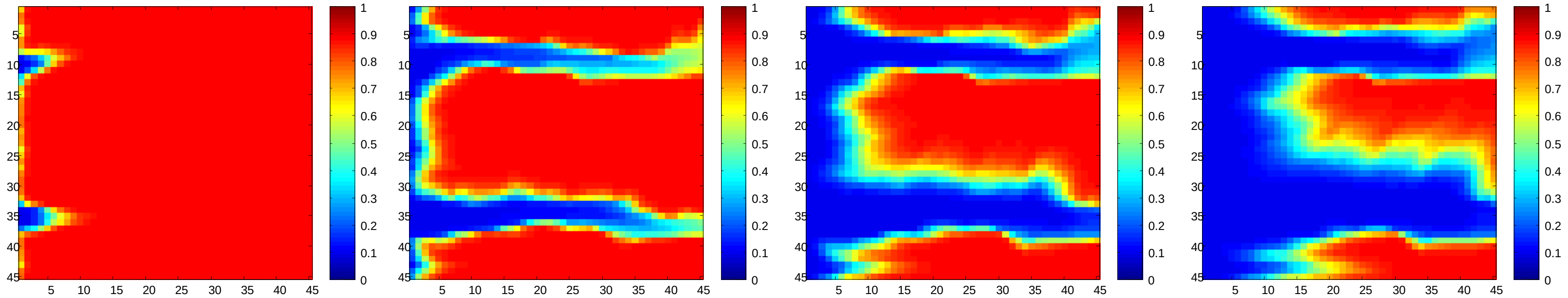


Brouwer and Jansen, 2004, SPEJ

Results; conventional production

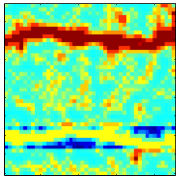


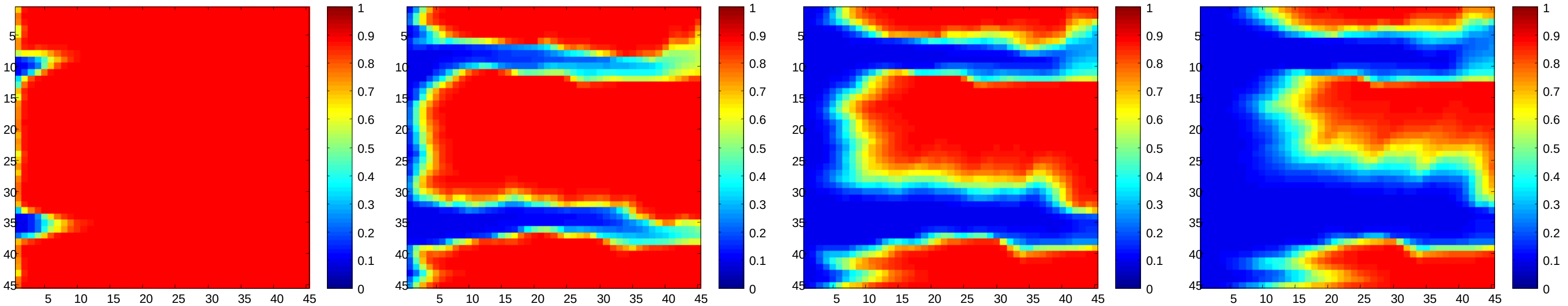




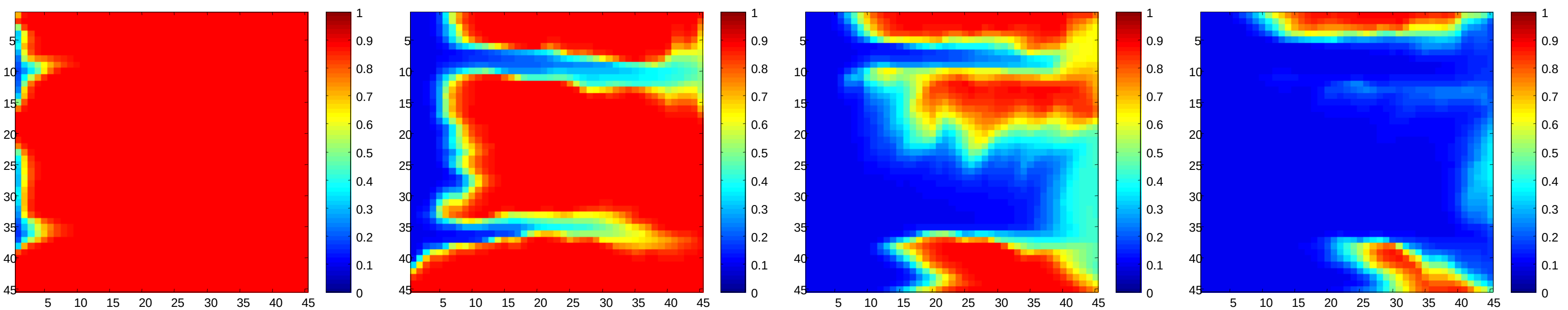
Equal pressures in all injector/producer segments

Results; rate-constrained (1)



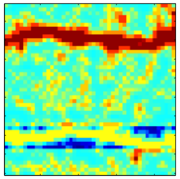


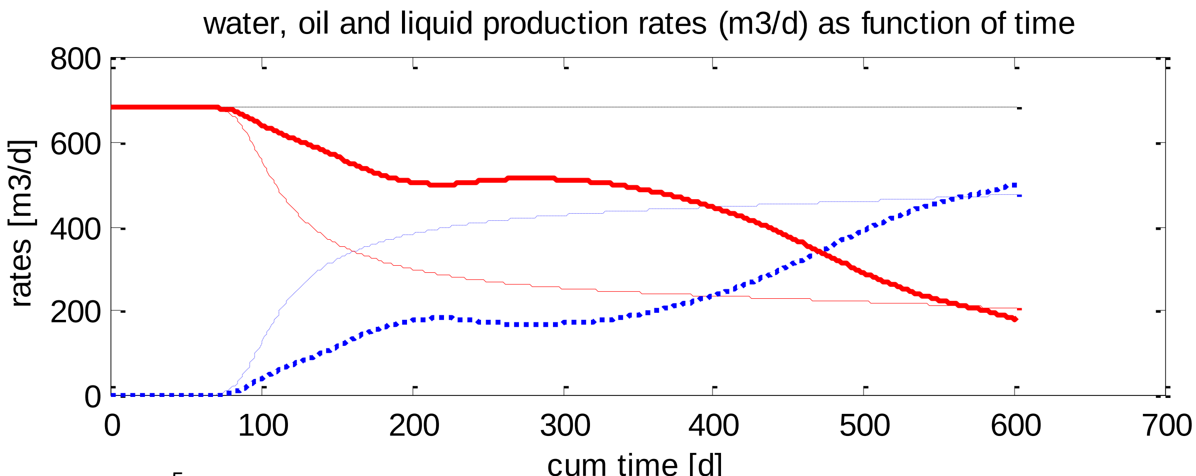
Conventional (equal pressure in all segments, no control)



Best possible (identical total rates, no pressure constraints)

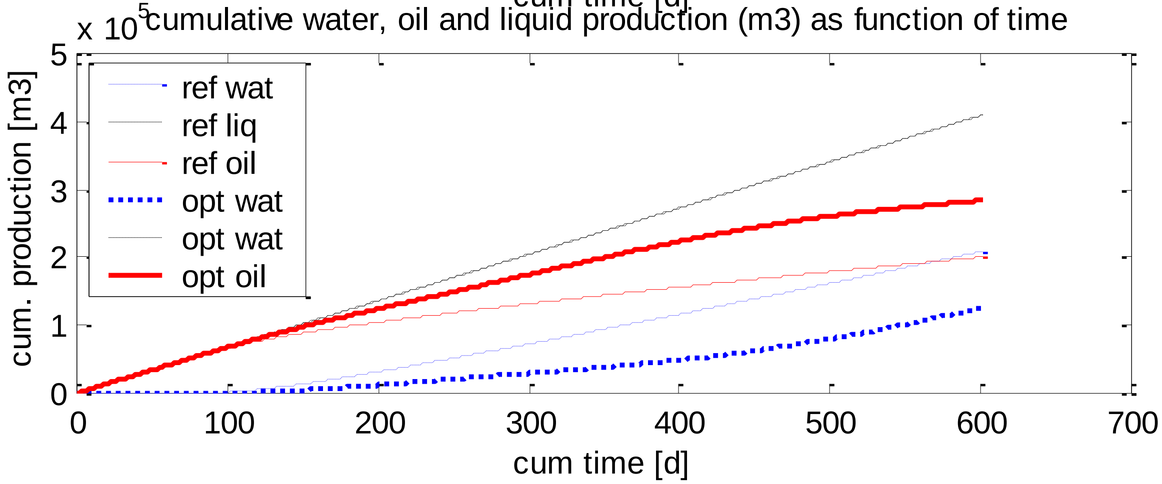
Results; rate-constrained (2)





NPV

+60%

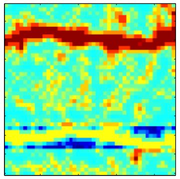


Production

+ 41% cum oil

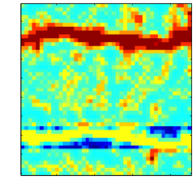
- 45% cum wat

Pressure-constrained operation



- Limited energy available
- Total injection/production rate dependent on number of active wells

Results: pressure-constrained



Improvement in NPV

+53%

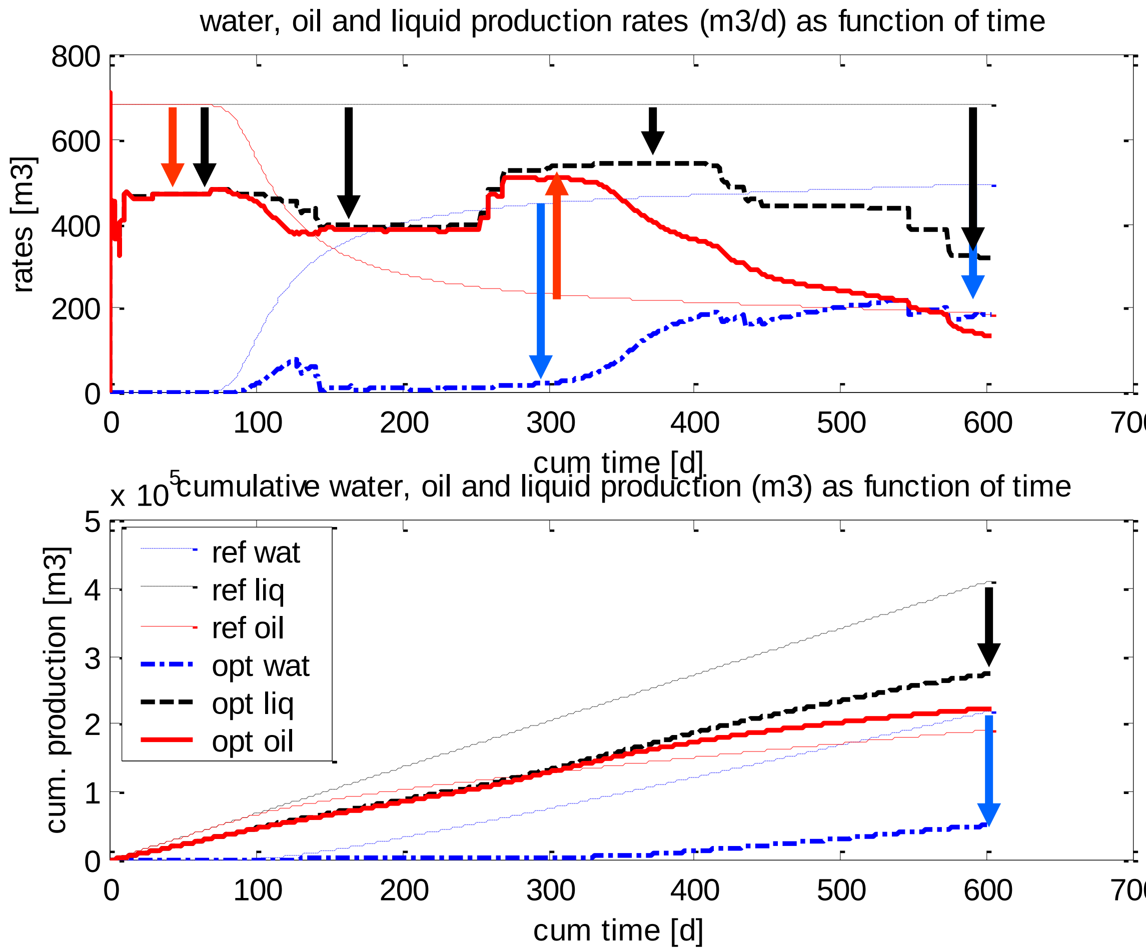
Production

+16% cum oil

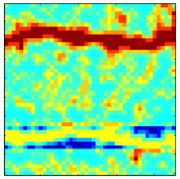
-77% cum water

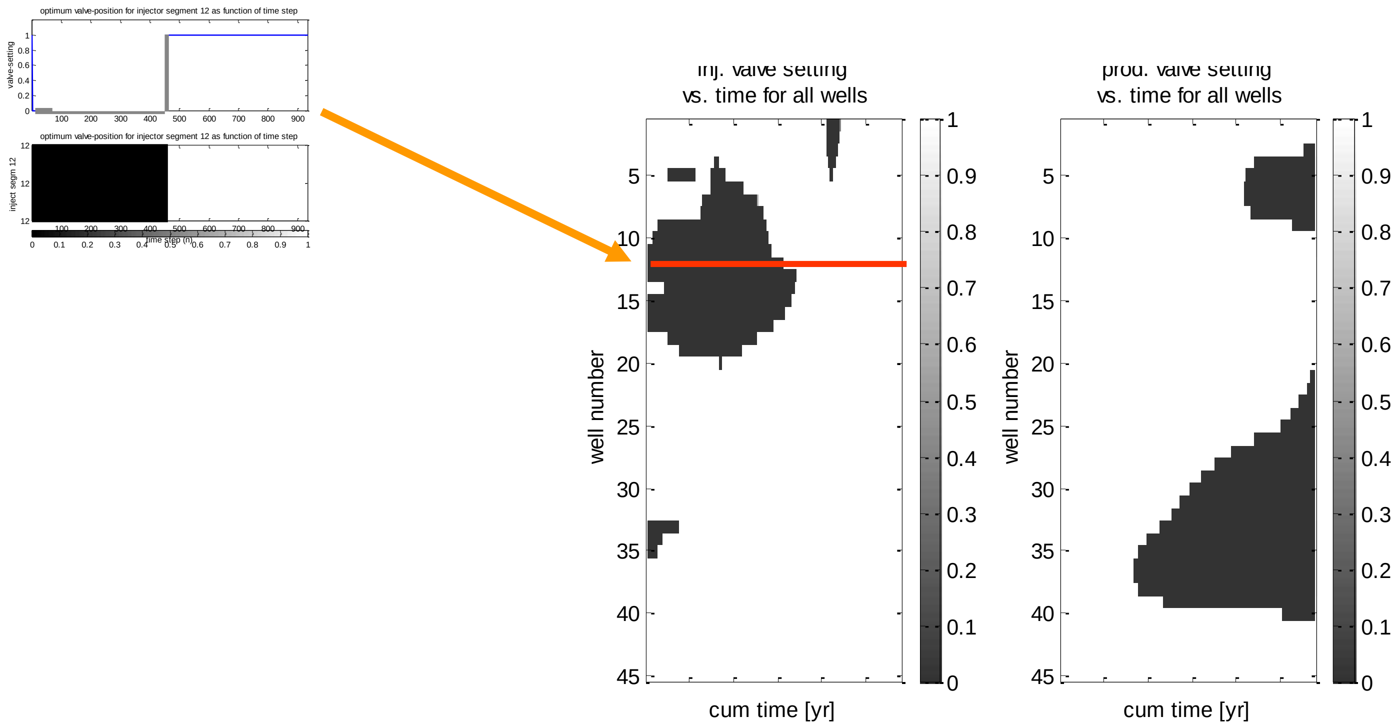
Injection

-32% cum water



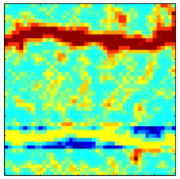
Optimum valve-settings (1)

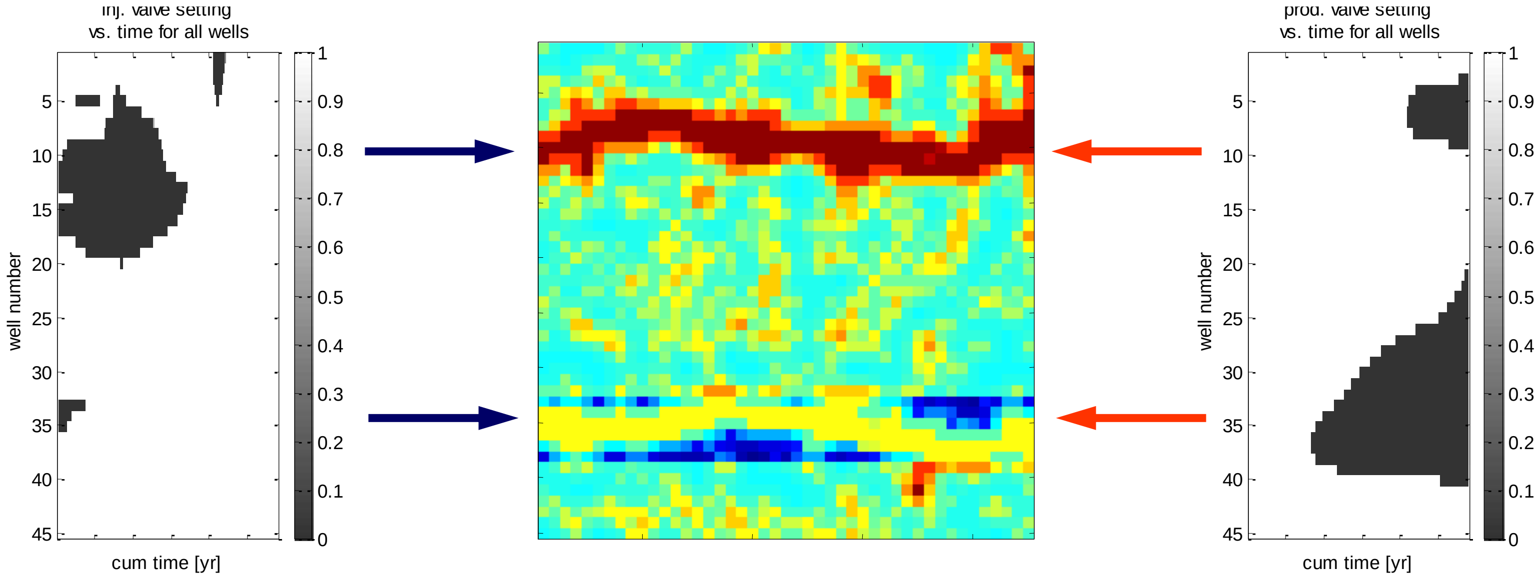




- Bang-bang (on-off) solution
- Necessary condition: linear controls, linear constraints

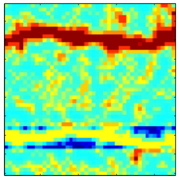
Optimum valve-settings (2)

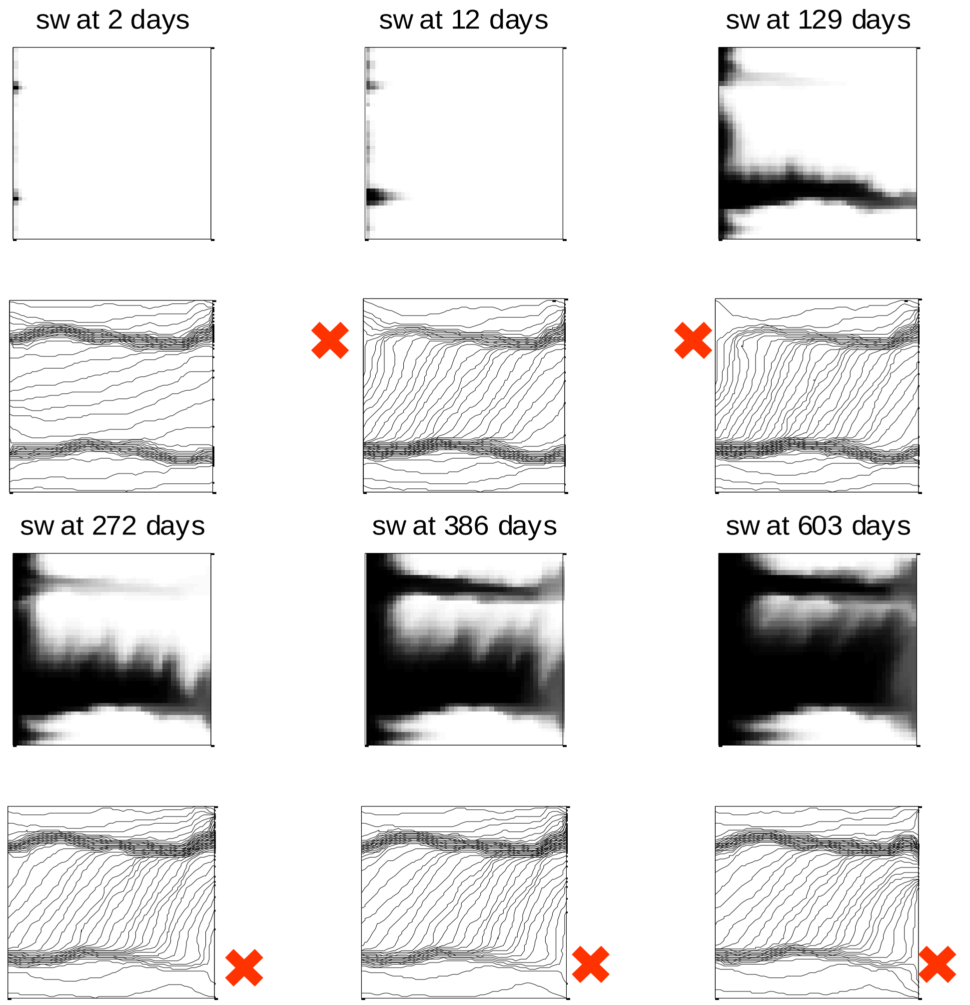




All the action is around the heterogeneities

Optimum valve settings (3)

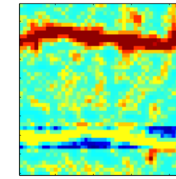




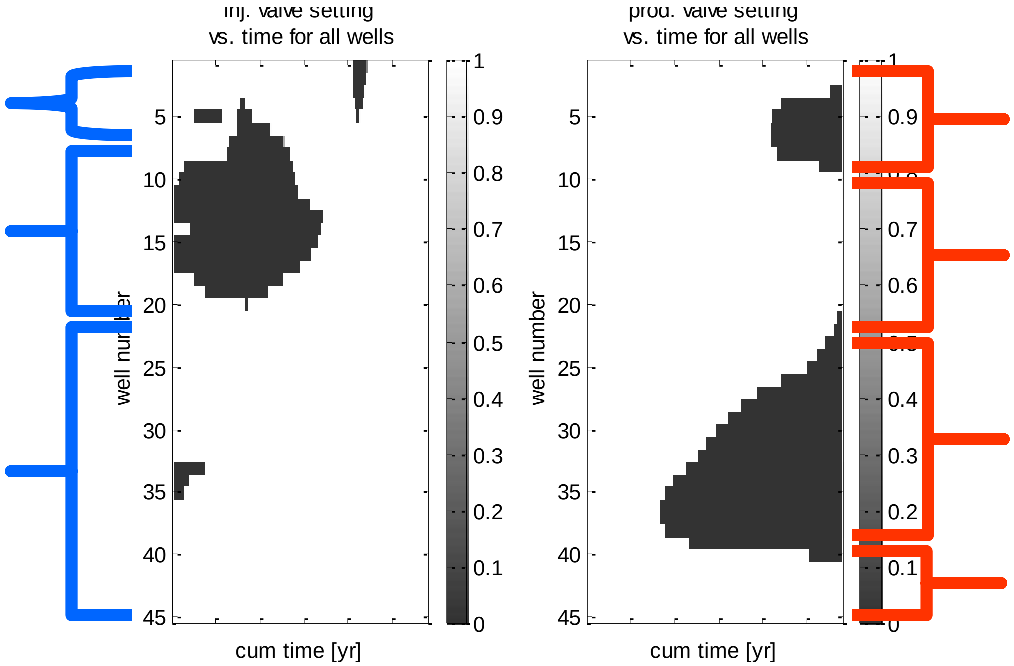
Streaks act as well extensions

Presence of heterogeneities essential for optimization

Optimum valve-settings (4)



3 valves in injector

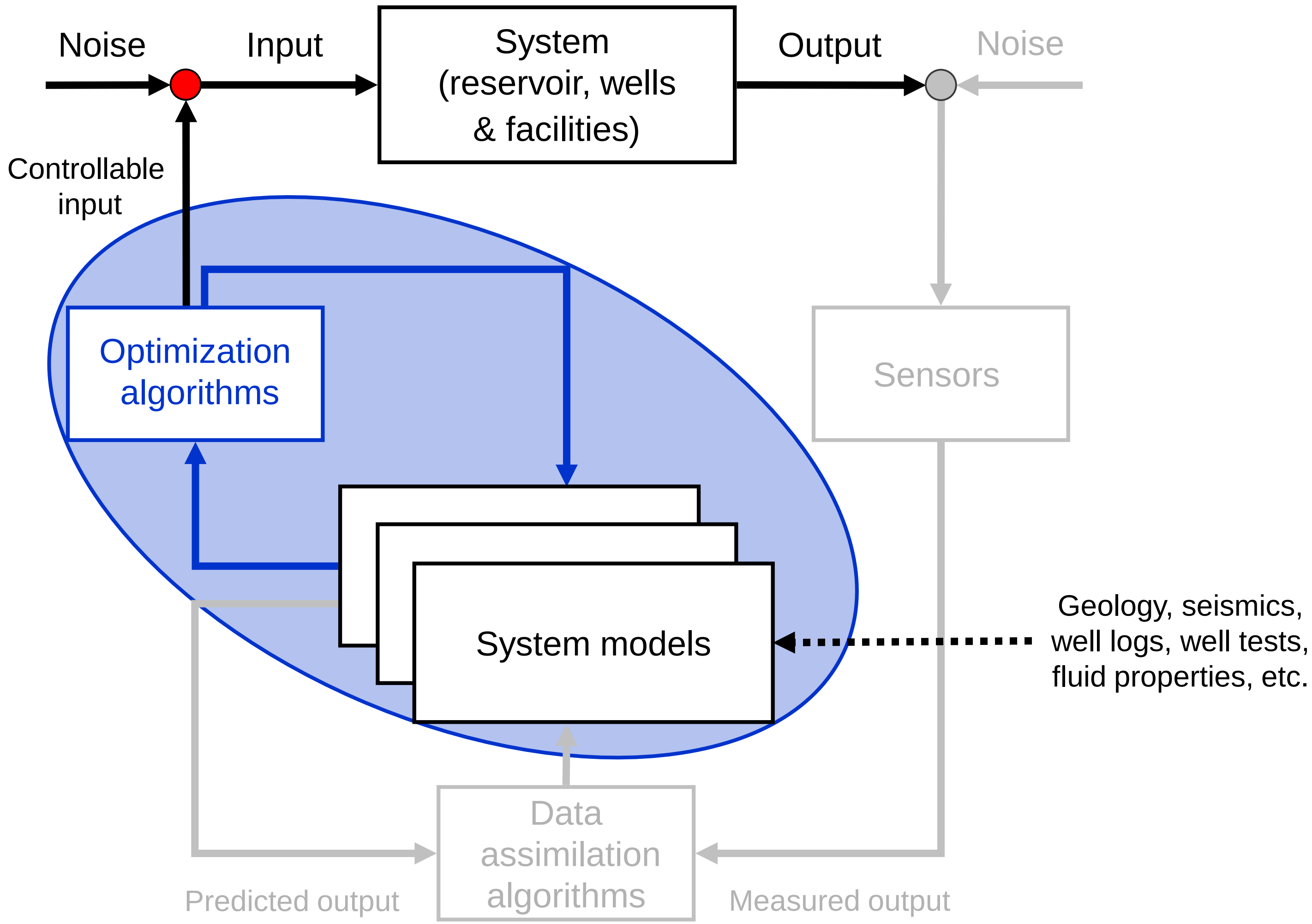


4 valves in producer

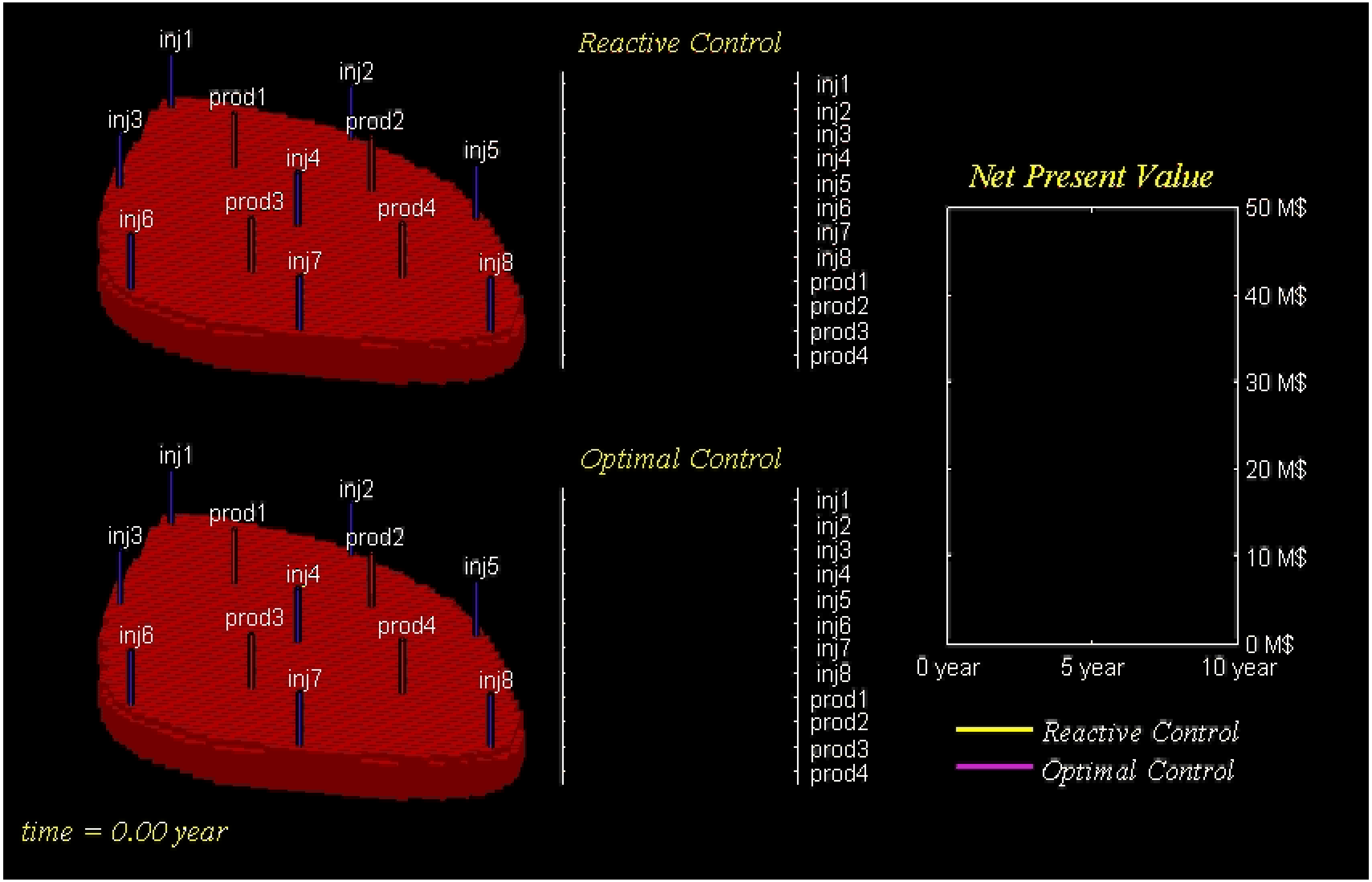
No need for 45 segments per well

Van Essen et al., 2010: Optimization of smart wells in the St. Joseph field.
SPE REE **13** (4) 588-595. DOI: 10.2118/123563-PA.

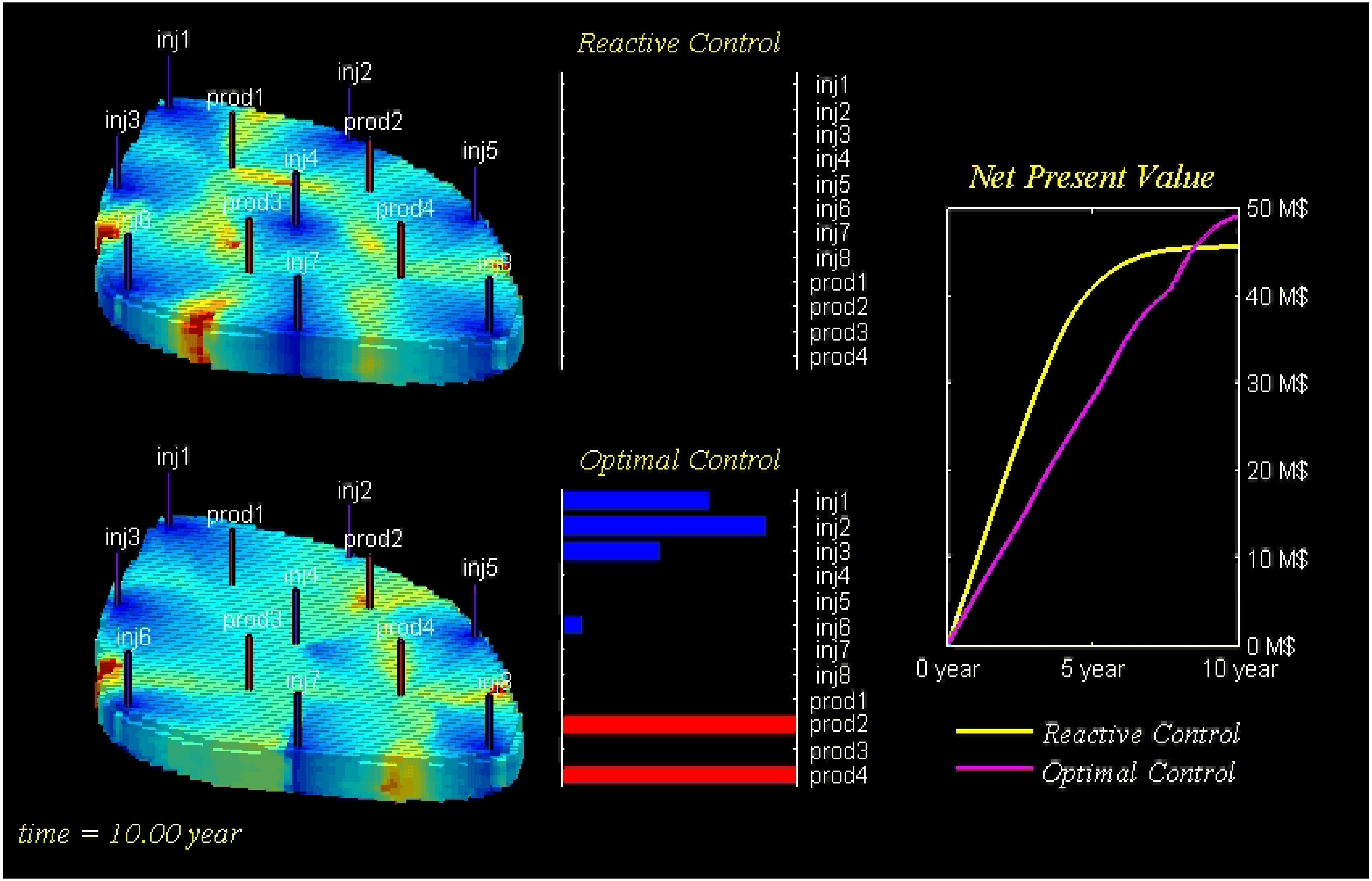
Link with short-term optimization



Life-cycle optimization vs. reactive control (1)

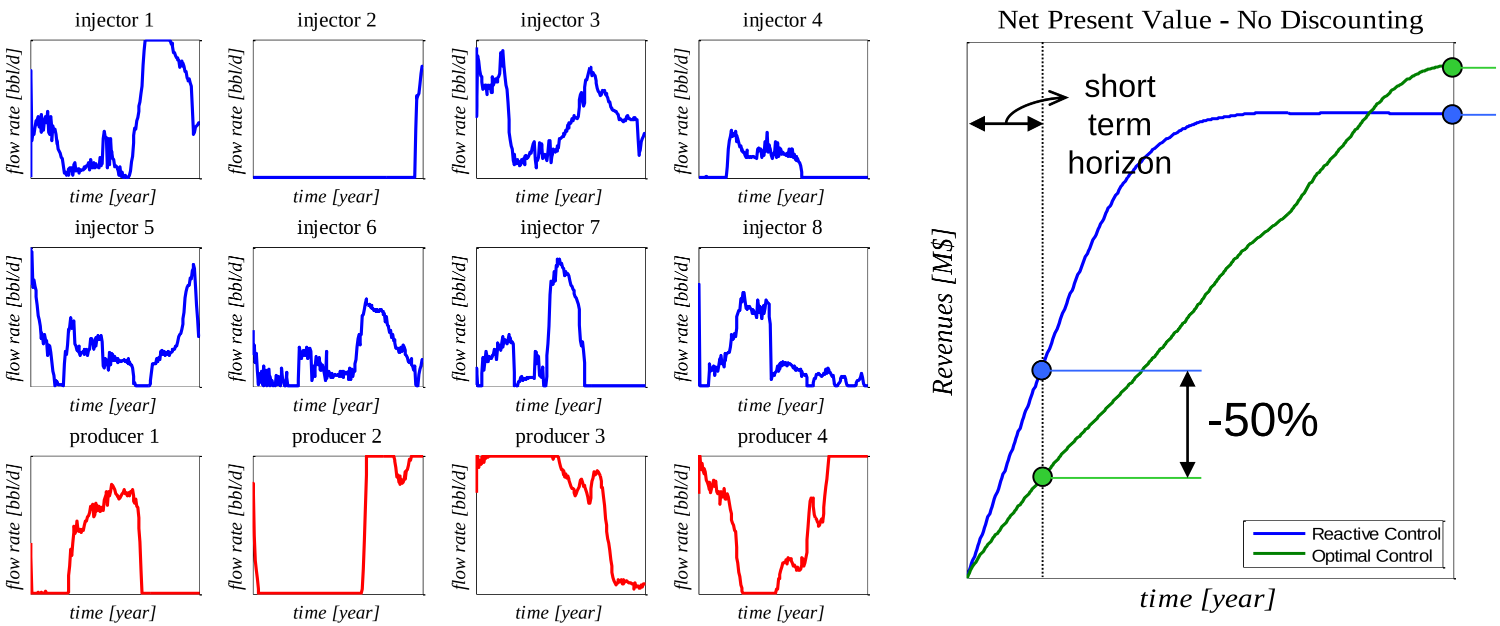


Life-cycle optimization vs. reactive control (2)



Life-cycle optimization vs. reactive control (3)

- Life-cycle optimization attractive for reservoir engineers
  - Increased NPV due to improved sweep efficiency



Van Essen et al., 2011, SPEJ

- Not so attractive from production engineering point of view
  - Decreased short term production
  - Erratic behavior of optimal operational strategy

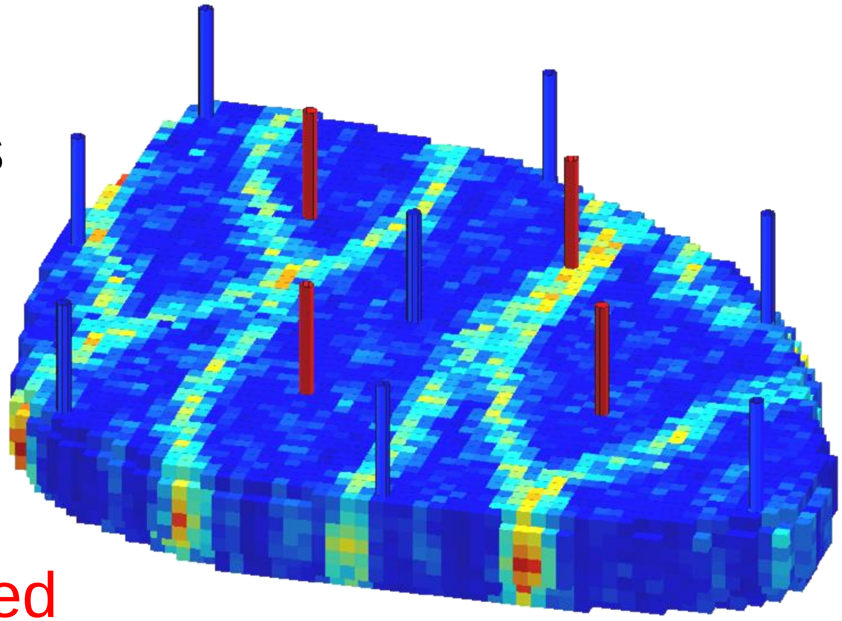
Hierarchical optimization

- Take production objectives into account by incorporating them as additional optimization criteria:
- Formal solution:
  - Order objectives according to importance
  - Optimize objectives sequentially
  - Optimality of upper objective constrains optimization of lower one
- Only possible if there are redundant degrees of freedom in input parameters after meeting primary objective

Objective function with ridges

Example: Hierarchical optimization using null-space approach (1)

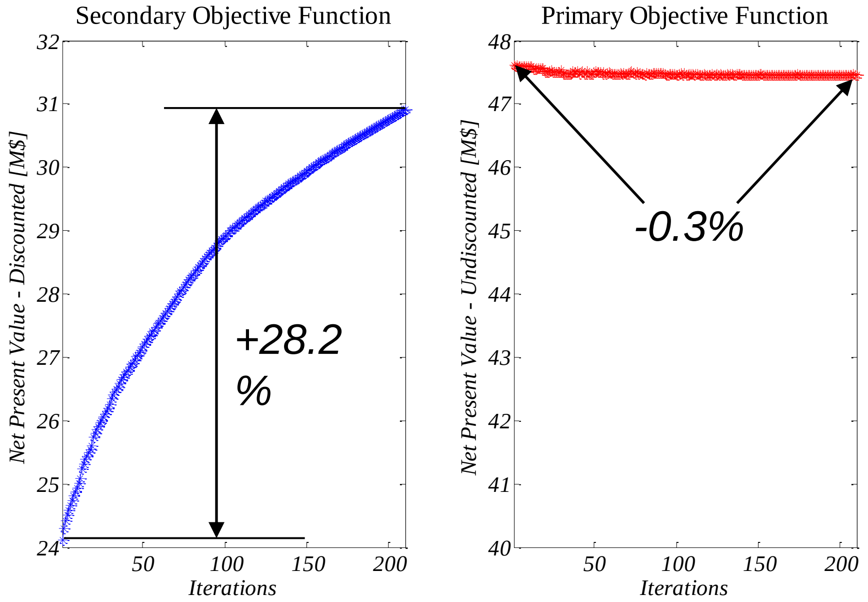
- 3D reservoir
- 8 injection / 4 production wells
- Period of 10 years
- Producers at constant BHP
- Rates in injectors optimized



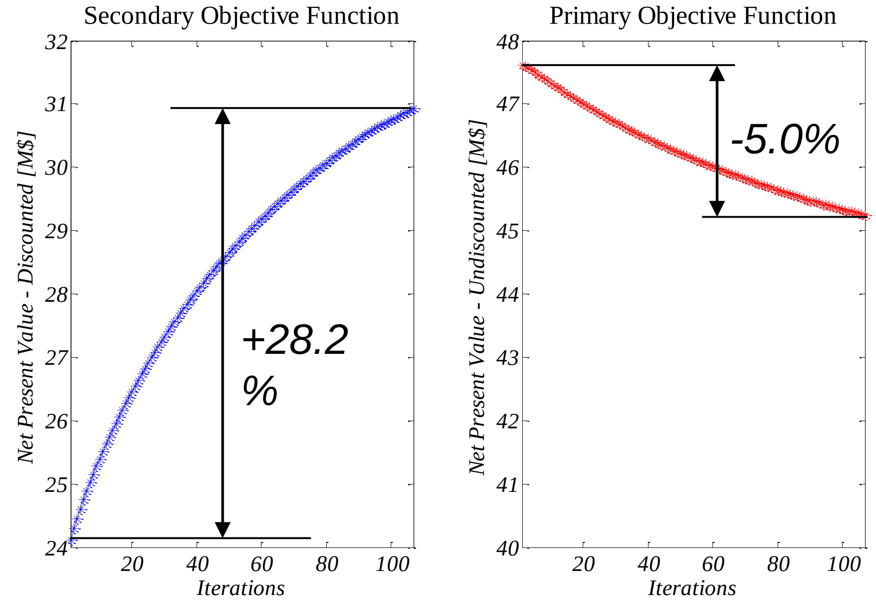
- *Primary objective*: undiscounted NPV over the life of the field
- *Secondary objective*: NPV with very high discount factor (25%) to emphasize importance of short term production

Example: Hierarchical optimization using null-space approach (2)

Optimization of secondary objective function - constrained to null-space of primary objective

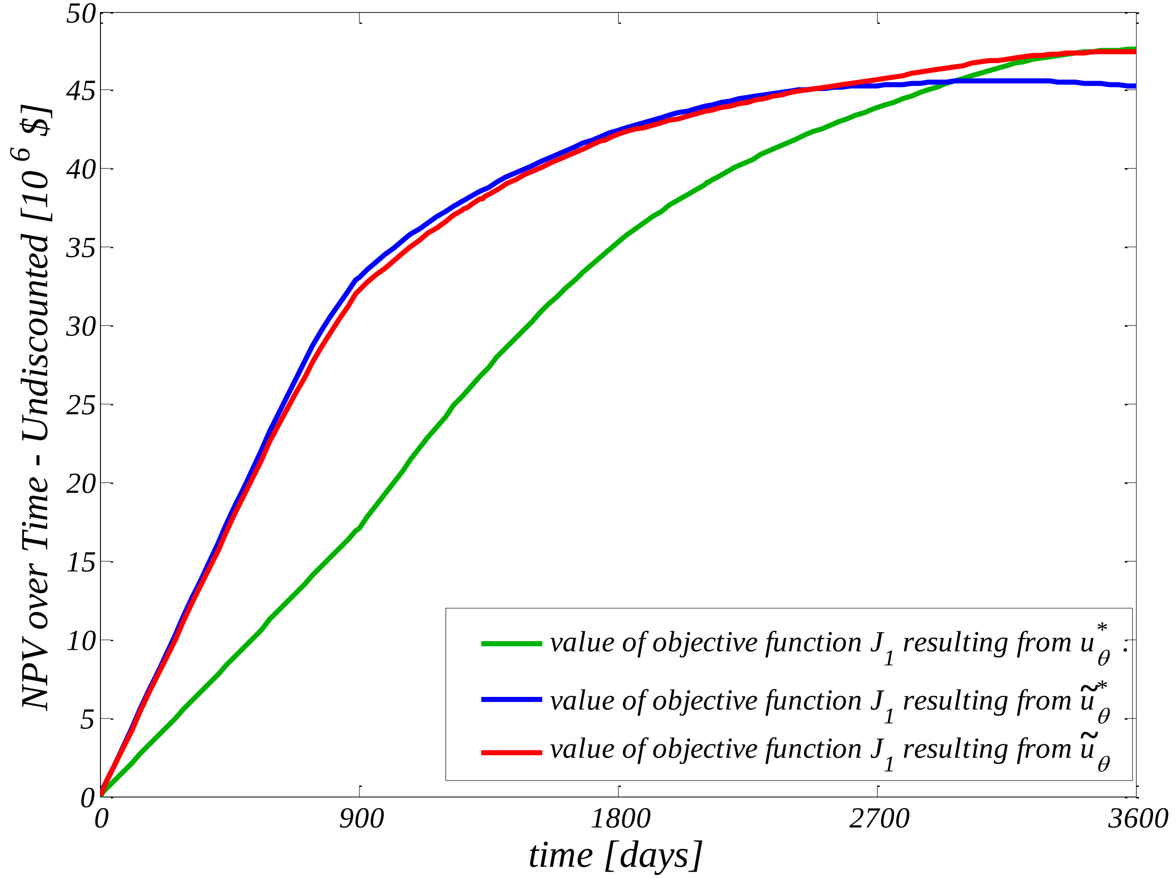


Optimization of secondary objective function - unconstrained



Van Essen et al., 2011, SPEJ

Example: Hierarchical optimization using null-space approach (3)



Model based optimization – Conclusions (in 2017)

‘Well control’ optimization :

- Adjoint-based techniques work well; constraints, regularization, storage, efficiency, still to be improved
- Streamlines, gradient-free, particle swarms, EnOpt, StoSAG

Well location optimization (not discussed):

- Gradient-free seems to work best
- Combination with rate optimization

Field implementation:

- Well control optimization: none reported
- Acceptance will require combi with short-term optimization
- Computer-assisted history matching: thriving!
- Well location/trajectory optimization: up and coming!
- Advisory mode – tools for discussion

Acknowledgments

- Colleagues and students of
  - TU Delft – Department of Geoscience and Engineering
  - TU Eindhoven (TUE) – Department of Electrical Engineering
  - TU Delft – Delft Institute for Applied Mathematics
  - TNO – Built Environment and Geosciences

- Especially for the optimization results presented in this overview: Prof. Paul Van den Hof (TUE), Prof. Arnold Heemink (TUD), and (former) PhD students Roald Brouwer, Maarten Zandvliet and Gijs van Essen

- Sponsors:
  - Shell: VALUE, 2003-2008; ISAPP 1 (with TNO) 2005-2009; Recovery Factory, 2010-2016
  - ENI, Petrobras, Statoil: ISAPP 2 (with TNO), 2011-2017

Ensemble Optimization

Theory and applications

Olwijn Leeuwenburgh[1,2]

[1] TNO

[2] Delft University of Technology

NIOR Workshop on Data Assimilation, Optimization and Uncertainty Quantification, 2021

Problem definition

- Problem definition

objective function (monetary value)

control vector (parameterizing the operational or development strategy)

$$\min_x \quad f(x)$$

$$\text{s.t.} \quad c_e(x) = 0$$ equality constraint functions

$$c_i(x) \leq 0$$ inequality constraint functions

$$a \leq x \leq b$$ lower and upper control bounds

- Solution $\hat{x} = \arg\min_x f(x)$
- Solution approach: iterative gradient-based minimization

approximate gradient

$$x_{k+1} = x_k + \alpha_k s_k(\beta_k)$$

search direction

Stochastic approximation

- Stochastic approximation for nonlinear root finding (Robbins and Monro, 1951)

system of n nonlinear equations in x

$$g(x) = 0$$

- RM51 assumed availability of a noisy estimate

$$\beta_k = g(x_k) + \epsilon_k(x_k)$$

noise vector

- and adopted a solution strategy

$$x_{k+1} = x_k - \alpha_k \beta_k$$

gain (step size)

- Sufficient conditions for convergence were formulated in the 50's and 70's (gain sequence, noise, direction of estimate)
- For unconstrained function optimization: $g(x) = \nabla f(x) = 0$

Directional derivatives

- Function approximation by Taylor series expansion ($|\Delta x| = 1$)

$$f(x + c\,\Delta x) = f(x) + c\;\Delta x^T \nabla f(x) + \frac{1}{2} c^2 \Delta x^T \nabla^2 f(x) \Delta x + \mathcal{O}(c^3)$$

- Centered directional derivative

$$\frac{f(x + c\,\Delta x) - f(x - c\,\Delta x)}{2c} = \Delta x^T \nabla f(x) + \mathcal{O}(c^2)$$

- Finite difference gradient estimate: $\Delta x = c\;e_i$

$$\beta_i = \frac{f(x + c\;e_i) - f(x - c\;e_i)}{2c} \approx e_i^T \nabla f(x) = \frac{\partial f(x)}{\partial x_i}$$

RDSA

- Random Direction Stochastic Approximation (Ermoliev, 1969)
- Define $\Delta x = p$

random direction

$$\beta = p \, \frac{f(x + c\,p) - f(x - c\,p)}{2c}$$

- Expected value

$$\mathbb{E}[\beta_i] = \mathbb{E}[p_i \, \frac{f(x + c\,p) - f(x - c\,p)}{2\,c}]$$

$$\approx \mathbb{E}[p_i \, \frac{f(x) + c\,p^T\,\nabla f(x) - f(x) + c\,p^T\,\nabla f(x)}{2\,c}]$$

$$= \mathbb{E}[\frac{2\,c\sum_{j=1}^{n} \frac{\partial f(x)}{\partial x_j} p_j\; p_i}{2\,c}]$$

$$= \frac{\partial f(x)}{\partial x_i}\mathbb{E}[p_i\,p_i] + \sum_{j \neq i} \frac{\partial f(x)}{\partial x_j}\mathbb{E}[p_j\,p_i] + \mathcal{O}(c^2)$$

SPSA

- Simultaneous Perturbation Stochastic Approximation (Spall, 1992).

$$\beta = \tilde{p}\,\frac{f(x + c\,p) - f(x - c\,p)}{2c} \quad \text{with} \quad \tilde{p} = [p_1^{-1}, p_2^{-1}, \ldots, p_n^{-1}]^T$$

- Expected value

$$\mathbb{E}[\beta_i] \approx \mathbb{E}[\frac{2\,c\,p^T\,\nabla f(x)}{2\,c\,p_i}] + \mathcal{O}(c^2)$$

$$= \mathbb{E}[\frac{2\,c\sum_{j=1}^{n}\frac{\partial f(x)}{\partial x_j}p_j}{2\,c\,p_i}] + \mathcal{O}(c^2)$$

$$= \frac{\partial f(x)}{\partial x_i} + \sum_{j\neq i}\frac{\partial f(x)}{\partial x_j}\mathbb{E}[\frac{p_j}{p_i}] + \mathcal{O}(c^2)$$

- Used in combination with symmetric Bernoulli distribution and prescribed gain sequence

Generalized SPSA

- Li and Reynolds (2010) proposed a one-sided ensemble version of RDSA with Gaussian perturbations for history matching
- Lower-order estimate than RDSA at half the computational cost

$$\mathbb{E}[\beta_i] = \mathbb{E}[p_i \, \frac{f(x + c\,p) - f(x)}{c}]$$
$$= \frac{\partial f(x)}{\partial x_i}\mathbb{E}[p_i\, p_i] + \sum_{j \neq i} \frac{\partial f(x)}{\partial x_j}\mathbb{E}[p_j\, p_i] + \mathcal{O}(c)$$

- Average full gradient vector over an ensemble

$$\mathbb{E}[\beta] = \mathbb{E}[\frac{1}{N_e}\sum_{i=1}^{N_e} p^i \, \frac{f(x + c\,p^i) - f(x)}{c}]$$
$$\approx \mathbb{E}[\frac{1}{N_e}\sum_{i=1}^{N_e}(p^i p^{iT})]\nabla f(x) = C_{xx}\, \nabla f(x)$$

Stochastic noise reaction gradient

- Stochastic noise reaction (Koda and Okano, 2000).

$$\beta = \frac{1}{\sigma_p^2 N_e} \sum_{i=1}^{N_e} p^i f(x + p^i) - \frac{1}{\sigma_p^2} \left(\frac{1}{N_e} \sum_{i=1}^{N_e} p^i \right) f(x)$$

$$\underset{\sigma_p = 1, c = 1}{=} \frac{1}{N_e} \sum_{i=1}^{N_e} p^i \frac{f(x + c\,p^i) - f(x)}{c}$$

- Expected value (assuming $p^i \sim \mathrm{N}(0, \sigma_i^2)$)

$$\frac{1}{\sigma_i^2} \mathbb{E}[f(x+p)p_i] = \frac{1}{\sigma_i^2} \mathbb{E}\left[\left(f(x) + \sum_{k=1}^{\infty} \frac{1}{k!} \left(\sum_{j=1}^{n} p_j \frac{\partial}{\partial x_j} \right)^k f(x)\right) p_i\right]$$

$$= \frac{\partial f(x)}{\partial x_i} + \sum_{r=1}^{\infty} \frac{1}{r!} \left(\sum_{j=1}^{n} \left(\frac{\sigma_j}{\sqrt{2}} \right)^2 \frac{\partial^2}{\partial x_j^2} \right)^r \frac{\partial f(x)}{\partial x_i}$$

Simplex gradient

- Define the one-sided directional derivatives

$$\frac{f(x^1 + c\,\Delta x^i) - f(x^1)}{c} = \Delta x^{iT} \nabla f(x^1) + \mathcal{O}(c)$$

$c = 1 \quad \Delta x^i = x^i - x^1$

$$= f(x^i) - f(x^1) \approx (x^i - x^1)^T \nabla f(x)$$

element *i*-1 of *F* — row *i*-1 of *V*

- Kelley (1997): construct *F* and *V* with $i = 2, \ldots, n+1$ and solve

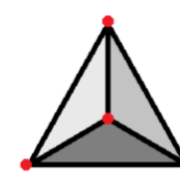
$$F \approx V \nabla f(x) \quad \rightarrow \quad \beta = V^{-1} F$$

- *V* must be nonsingular. Kelley (1997) used simplices of a Nelder-Mead algorithm and derived

simplex condition

$$\| \nabla f(x) - \beta \| \le K \cdot \kappa(V) \cdot \left(\max_{2 \le i \le n+1} \| x^i - x^1 \| \right)$$

simplex diameter



Ensemble gradient

- Chen (2008): use $N_e < n$ first-order random-directional derivatives and use ensemble-means as best guess.

Do and Reynolds (2013)

$\overline{x} = x$ and $\overline{f(x)} = f(x)$ with $x^i = x + p^i$

Element i of F — row i of X

- For each i = 1, …, N_e $\quad f(x^i) - f(x) \approx (x^i - x)^T \nabla f(x)$
- Regression $\quad F \approx X \nabla f(x) \quad \rightarrow \quad X^T F \approx (X^T X) \nabla f(x)$
- Gradient $\quad \beta = X^+ F \qquad \beta = (X^T X)^+ X^T F = \hat{C}_{xx}^+ \hat{C}_{xf}$
- Pre-conditioned gradient estimate (assuming $\mathbb{E}[p^i] = 0$)

$$\beta_{PC} = \frac{1}{N_e} X^T F \quad \rightarrow \quad \mathbb{E}[\frac{1}{N_e}(X^T F)] = \mathbb{E}[\frac{1}{N_e}(X^T X)] \nabla f = C_{xx} \nabla f(x)$$

Model uncertainty

- Consider that $f = f(x, m)$ and that we wish to minimize

$$\overline{f}(x, m) = \frac{1}{N_m} \sum_{j=1}^{N_m} f(x, m_j)$$

- Expected value gradient

$$\nabla_x \overline{f}(x, m) = \nabla_x \left(\frac{1}{N_m} \sum_{j=1}^{N_m} f(x, m_j) \right) = \frac{1}{N_m} \sum_{j=1}^{N_m} \nabla_x f(x, m_j)$$

- Alternative objectives were investigated by Capolei et al. (2013) and Siraj et al. (2016). Chen et al. (2017) used ensemble gradients.

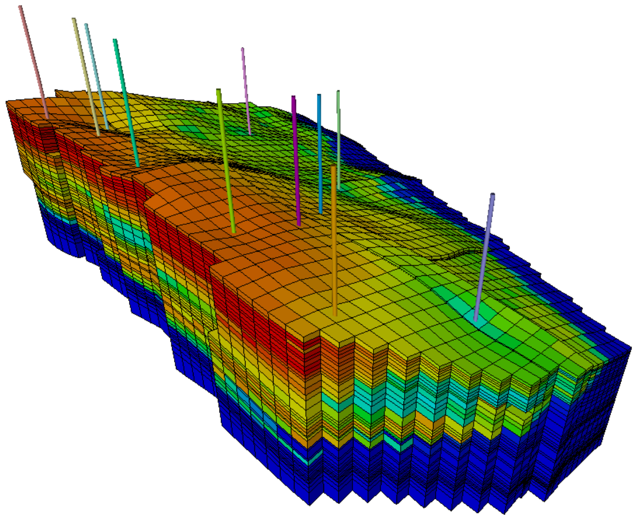
- Fonseca et al. (2014; 2017) introduced and analyzed StoSAG

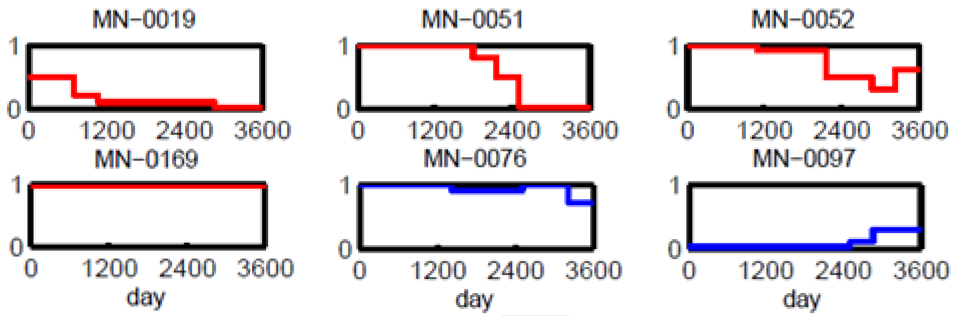
$$f(x_j^i, m_j) - f(x, m_j) \approx (x_j^i - x)^T \nabla_x f(x, m_j)$$

element i of $\tilde{F}$ ↑ ↑ row i of X

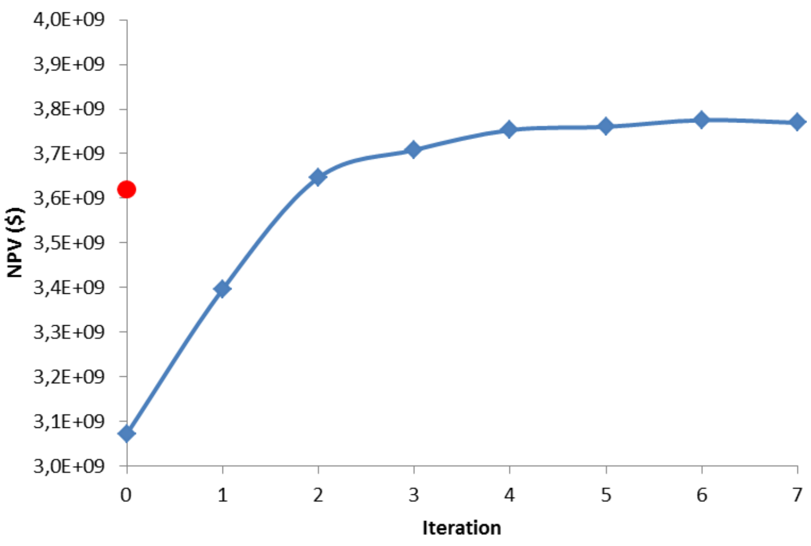
Real field application example

- Conventional wells
- 10-year life cycle with increased BHP
- 110 controls
- Reference case is reactive control





- 30% less water production
- 20% less water injection
- 4% higher NPV



Constrained ensemble optimization

- First addressed in ensemble context by Phale and Oliver (2014) for a deterministic problem.
- Problem definition *with uncertainty*

$$\min_{x} \quad \overline{f}(x, m)$$

$$\text{s.t.} \quad c_e(x, m_j) = 0 \quad \forall\, m_j, \quad j = 1, \ldots, N_m$$

$$c_i(x, m_j) \leq 0 \quad \forall\, m_j, \quad j = 1, \ldots, N_m$$

$$a \leq x \leq b$$

- Ensemble gradients of constraint functions can be obtained without additional cost!

Leeuwenburgh, Egberts, Chitu, and Alim SPE 174318, 2015.

Constraint gradient estimation

- Constraint functions can be evaluated for each perturbed input

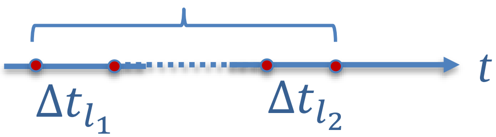
row i of C

$$c^l(x^i) - c^l(x) \approx (x^i - x)^T \nabla c^l(x)$$

- A gradient for each constraint function $c^l(x)$ can be estimated from

$$\beta_{c^l} = X^+ C$$

- Lumping is generally needed for constraints that should be met at each simulation time step, e.g.



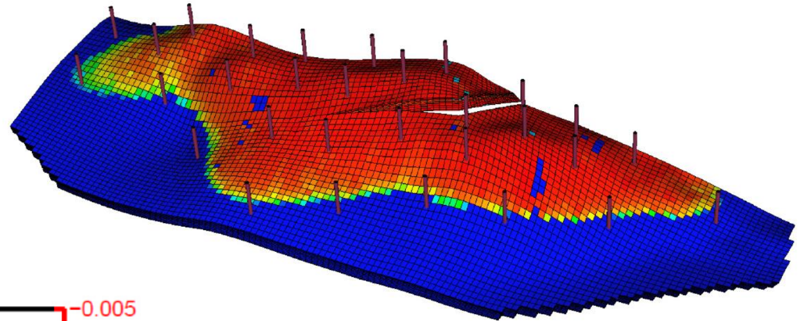
$$L(x) = \sum_{l=l_1}^{l_2} \max(c^l(x), 0) \leq 0$$

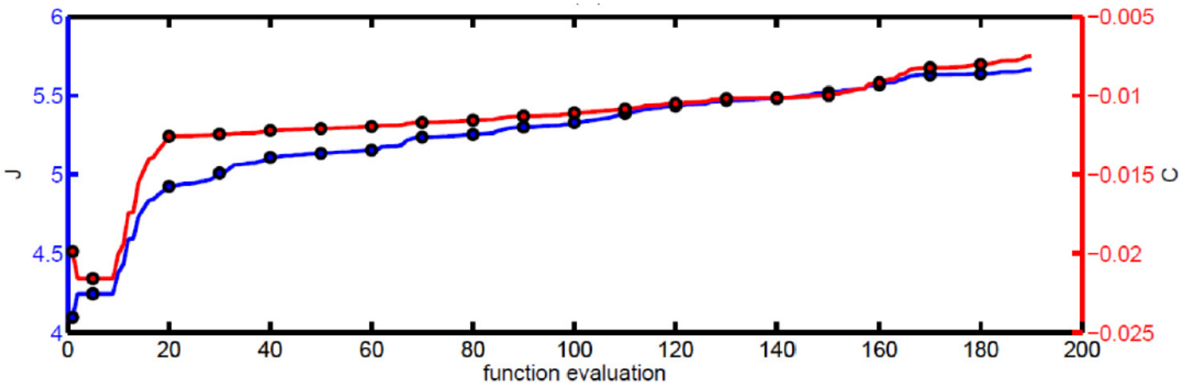
- With uncertainty present constraints could be imposed in the expected sense

$$\overline{L}(x) = \frac{1}{N_m} \sum_{j=1}^{N_m} \sum_{l=l_1}^{l_2} c^l(x, m_j) \leq 0$$

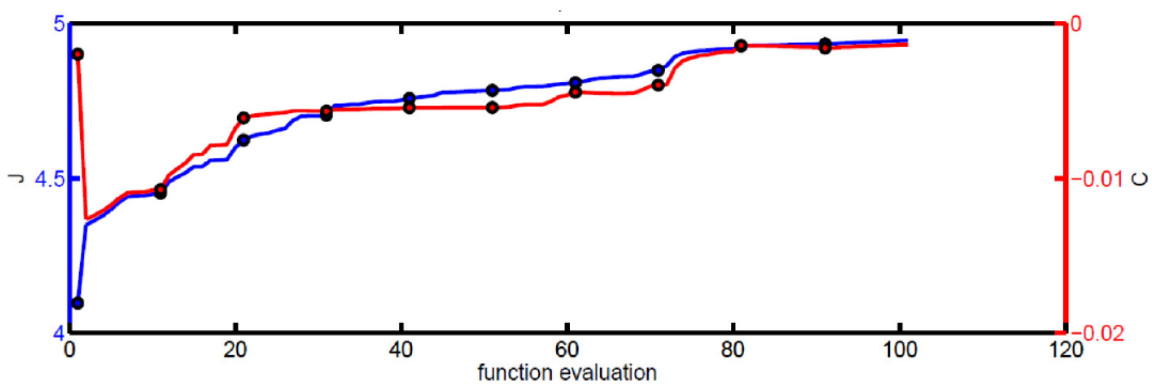
Brugge example

- Deterministic modified Brugge model
- 30 wells with total of 1740 ICV controls
- 20-year life cycle





20 lumped field injection constraints



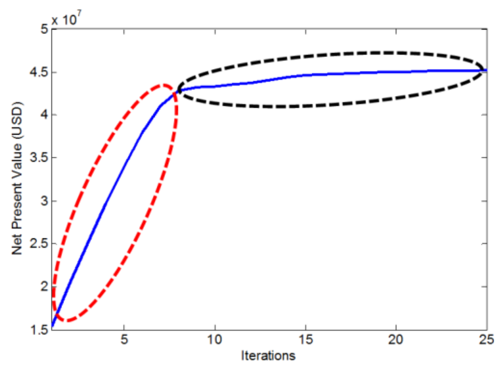
20 lumped field injection constraints + 600 lumped well rate constraints

Leeuwenburgh, Egberts, Chitu, and Alim SPE 174318, 2015.

Perturbation magnitude

- The quality of the gradient approximation and the rate of improvement in the objective may be expected to depend on the perturbation magnitude

- This dependence may be different at early and late stages of the optimization process



- StoSAG is normally applied using a fixed perturbation standard deviation

- Idea: use an adaptive sampling strategy in which the perturbation magnitude is updated

Covariance Matrix Adaptation

- CMA is an evolutionary strategy proposed by Hansen (2006)
- The covariance (mutation) matrix from which the new offspring is sampled is updated in each iteration
- Updates are based on μ best-performing samples
- Rank-μ update based on current iteration

$$\tilde{\mathbf{C}}_{uu}^{\ell+1} = (1 - c_\mu)\tilde{\mathbf{C}}_{uu}^{\ell} + c_\mu \frac{1}{\mu}\tilde{\mathbf{U}}\tilde{\mathbf{U}}^T$$

- Rank-1 update based on previous iterations

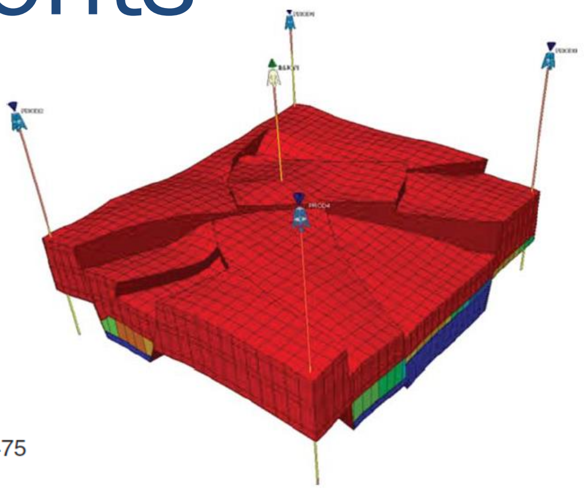
$$\tilde{\mathbf{C}}_{uu}^{\ell+1} = (1 - c_1)\tilde{\mathbf{C}}_{uu}^{\ell} + c_1 \mathbf{e}^{\ell+1}(\mathbf{e}^{\ell+1})^T$$

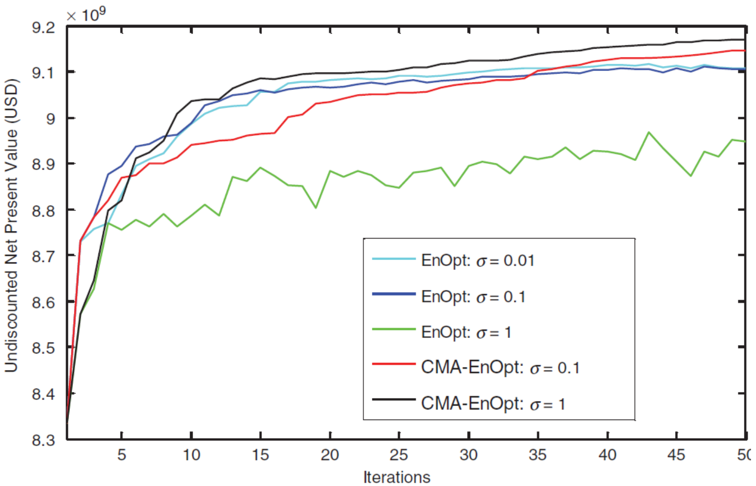
- Learning rates c have to be chosen by the user

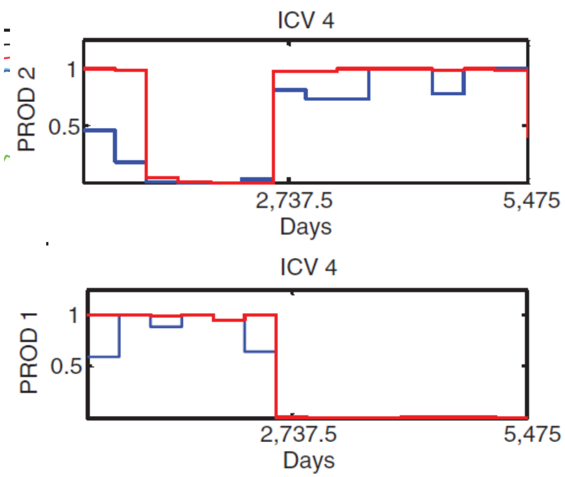
Fonseca, Leeuwenburgh, Van den Hof and Jansen, SPE J, 2015; Stordal, Szklarz, Leeuwenburgh (2016) : natural gradient with Gaussian mutation matrix

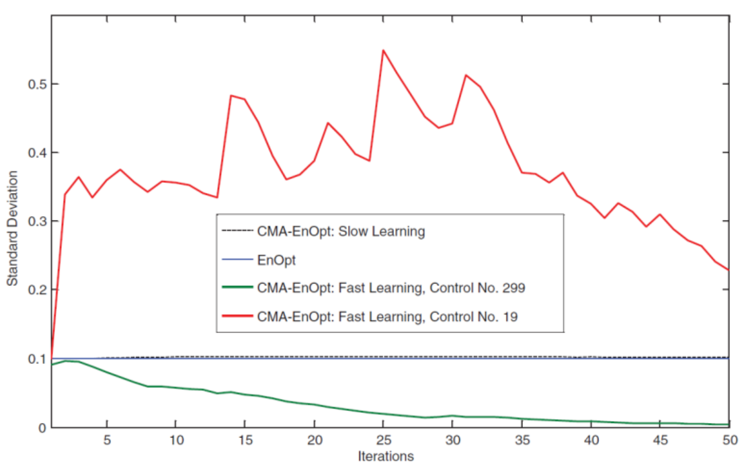
Numerical experiments

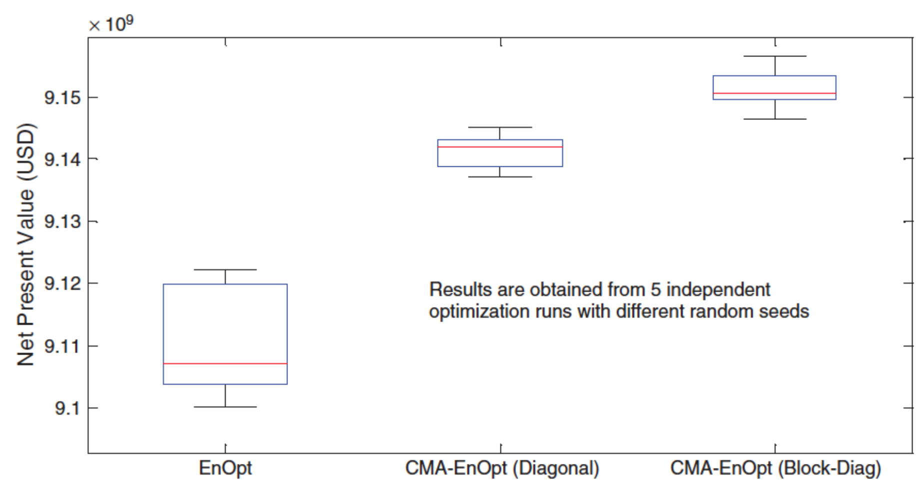
- ICV settings for multi-layer smart well











Optimal supersaturated designs

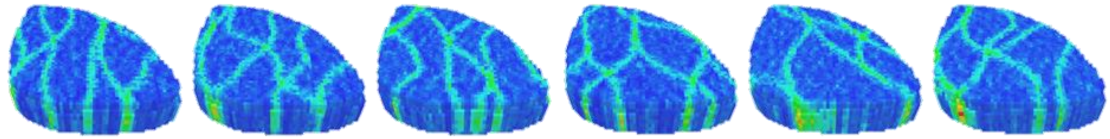
- Motivated by properties of solutions to underdetermined problems $F \approx X \nabla f(x)$
- Information matrix $S = X^T X$
- Optimal designs attempt to achieve near-orthogonality of S in order to minimize the variance of the estimator of $\nabla f(x)$
- Minimize $\max_{i \neq j} |s_{ij}|$, or, for $UE(s^2)$ optimal designs

$$UE(s^2) = \frac{2}{N(N-1)} \sum_{i<j} s_{ij}^2$$

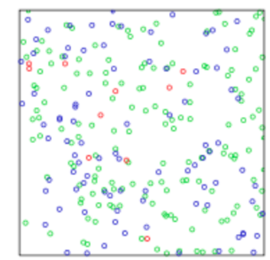
- $UE(s^2)$ optimal designs are also D-optimal – minimize the eigenvalue product of the estimator error covariance
- Construction of $UE(s^2)$ optimal designs is computationally expensive and difficult for $n > 2000$

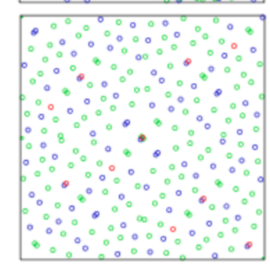
Ramaswamy, Fonseca, Leeuwenburgh, Siraj, Van den Hof (2020)

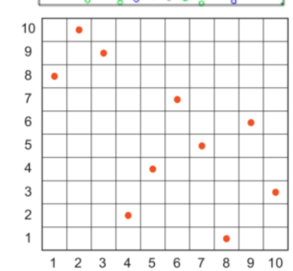
Numerical experiments



- 100 Egg models
- 320 injection rate controls
- Fixed perturbation standard deviation of 0.1
- Fixed step size of 0.1 for gradient norm of 1
- Sampling strategies
  - Multivariate Gaussian pseudo-random sampling
  - Quasi-random sampling (Sobol)
  - LHS designs
  - UE(s^2) designs
- Time correlation of 0 or 15 control intervals

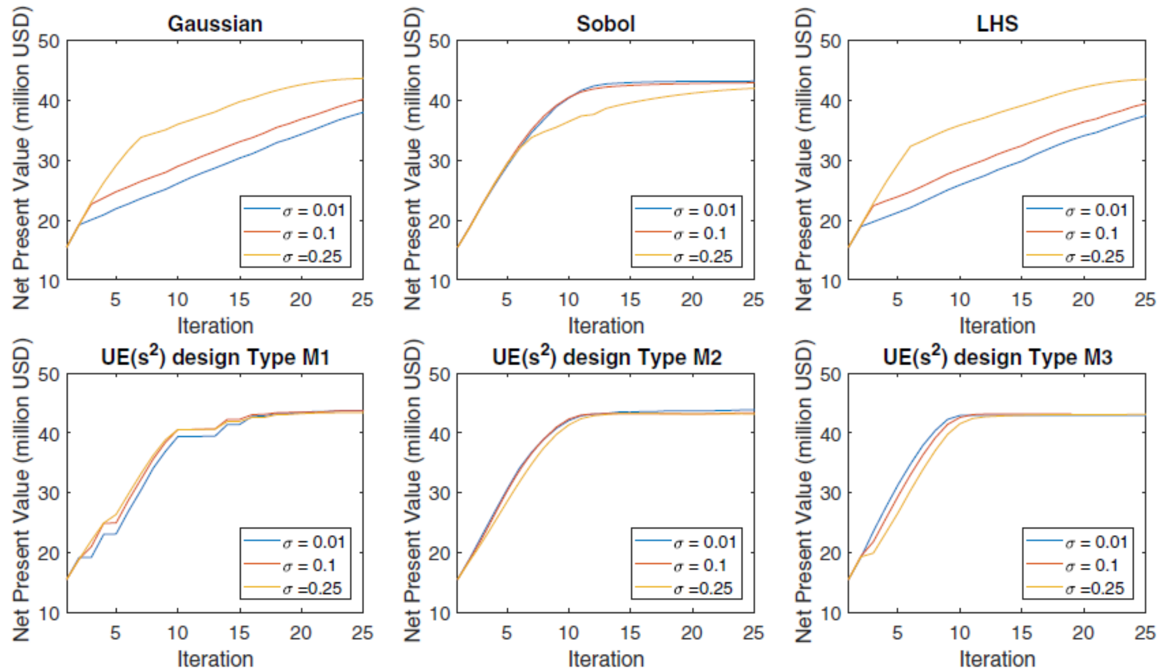


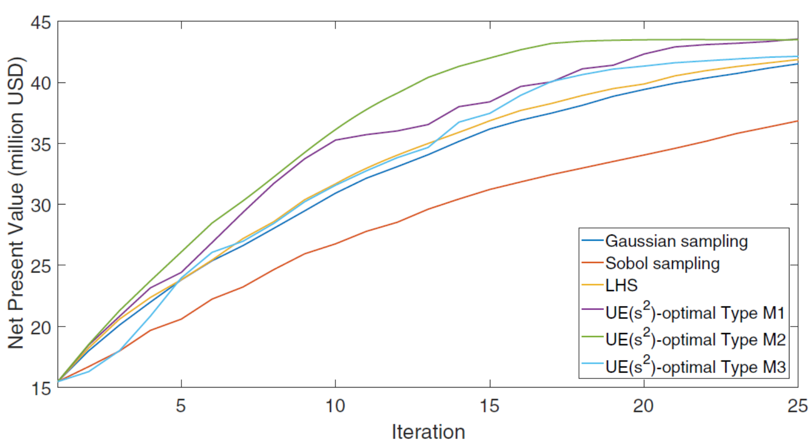




Results

- 3 variants of UE(s^2) sampling
- Robust optimization without perturbation smoothing





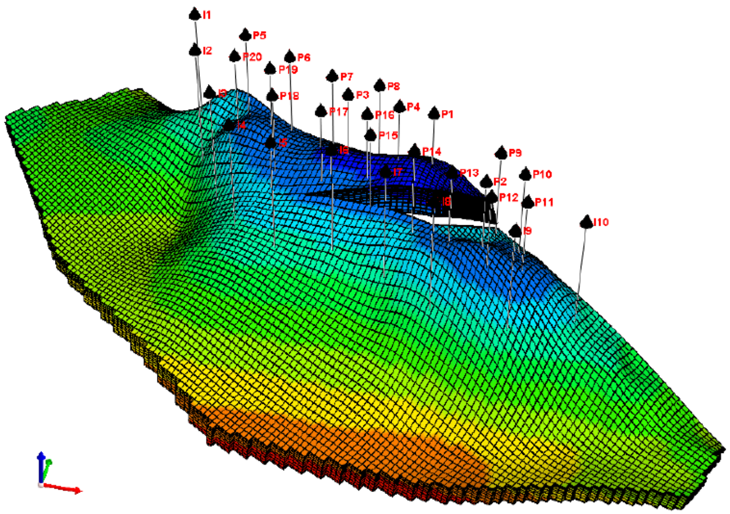
Sobol performance deteriorates when perturbations are smoothed

Risk measures

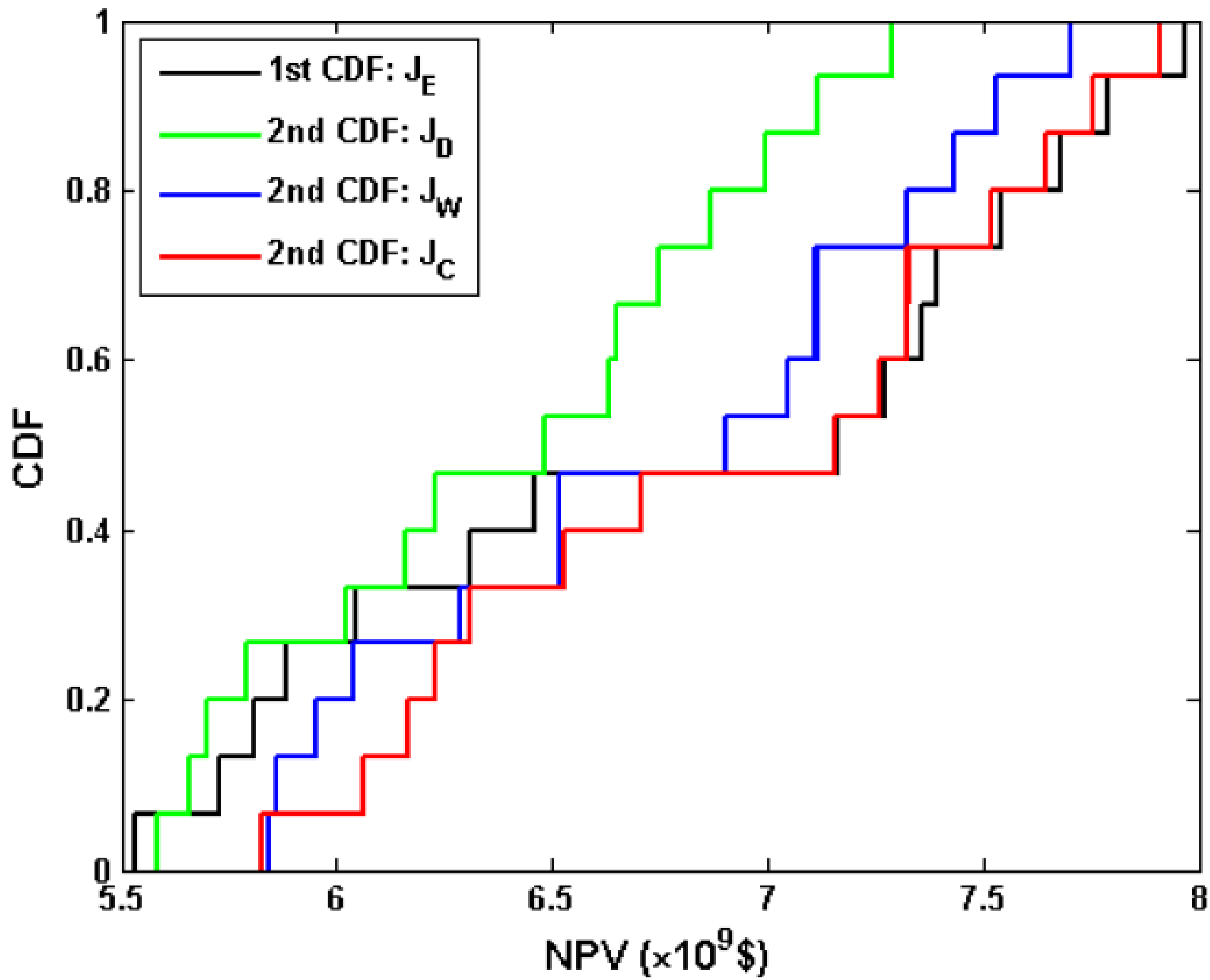
- Chen et al. (2017) performed optimization of various risk measures in a hierarchical framework using ensemble gradients and an augmented Lagrangian constraint treatment
  - Expected value
  - Worst case
  - Conditional value at risk (CVaR)
  - Standard deviation

$$J_C(u) = \frac{\sum_{i=1}^{N_Q} J(u, m_i)}{N_Q}$$

- Original Brugge model
- Controls: injector rates, producer BHP, andf ICV settings
- Comparison is done for a fixed number of simulations



Results

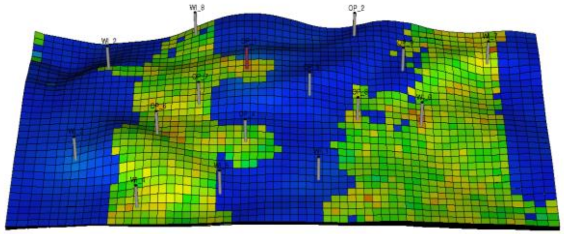


Chen, Fonseca, Leeuwenburgh, Reynolds, 2017.

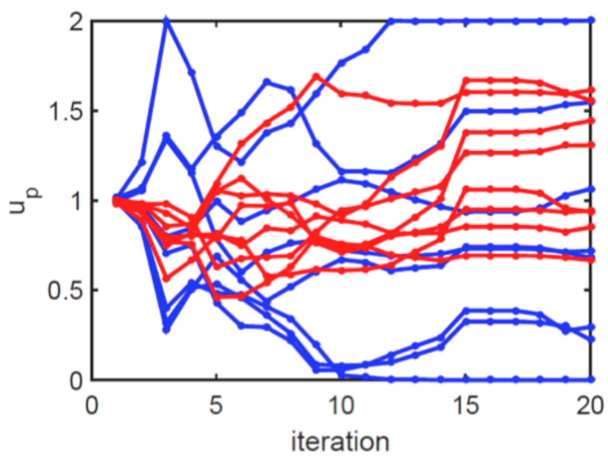
Non-continuous controls and functions

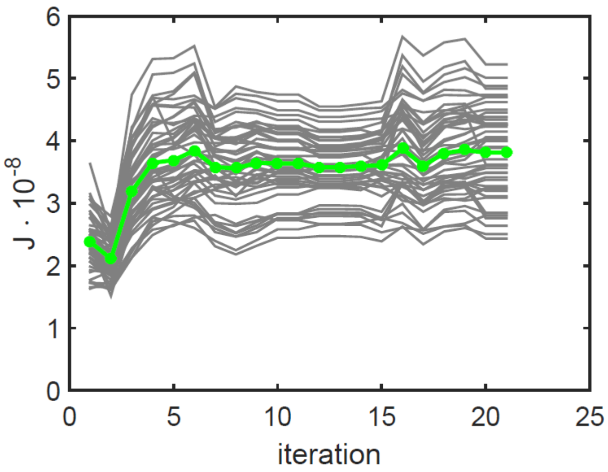
- Appear naturally in field development problems
- Example: drilling sequence, well type for fixed set of nominated wells
- Priority controls for well ordering:

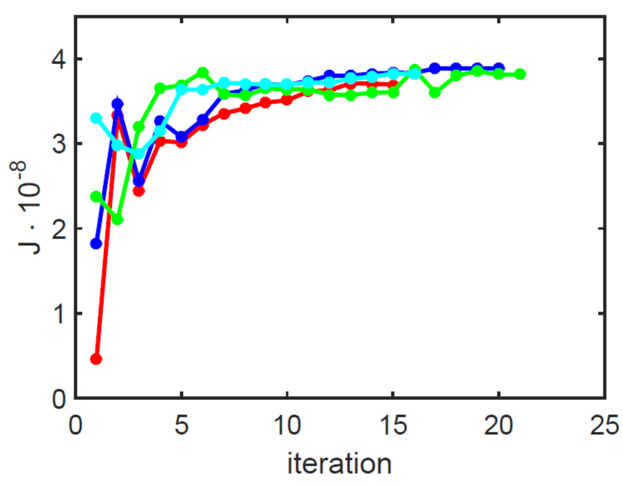
$$u_p = [0.1, 0.8, 0.5, 0.9] \longrightarrow \text{w4, w2, w3, w1}$$



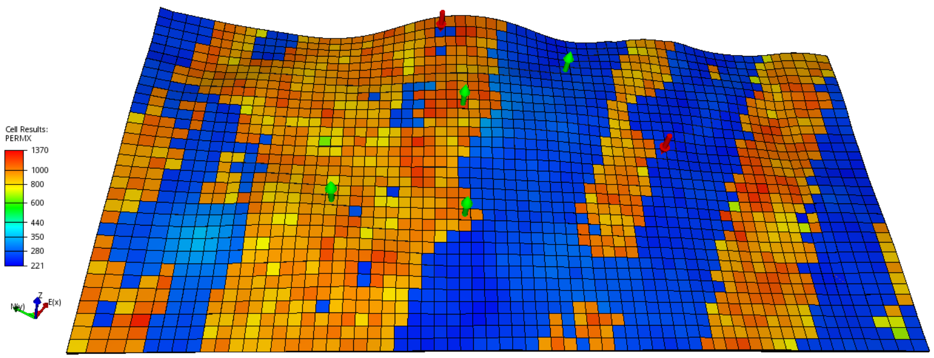
input-constrained J = 3.37 (+45%)

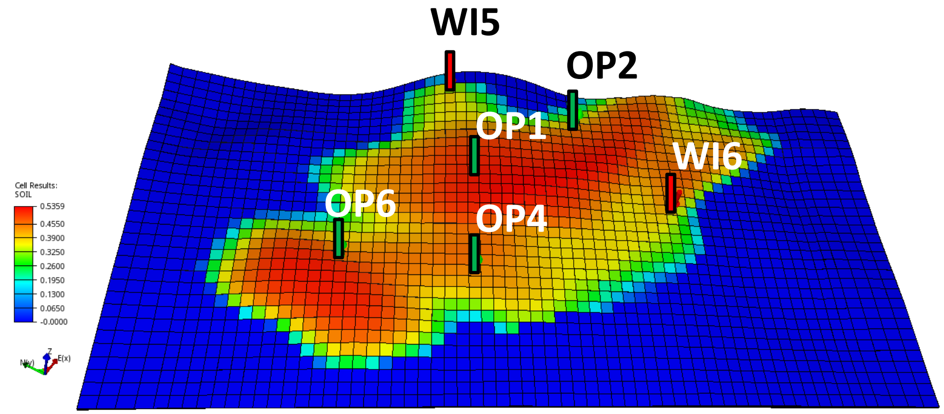




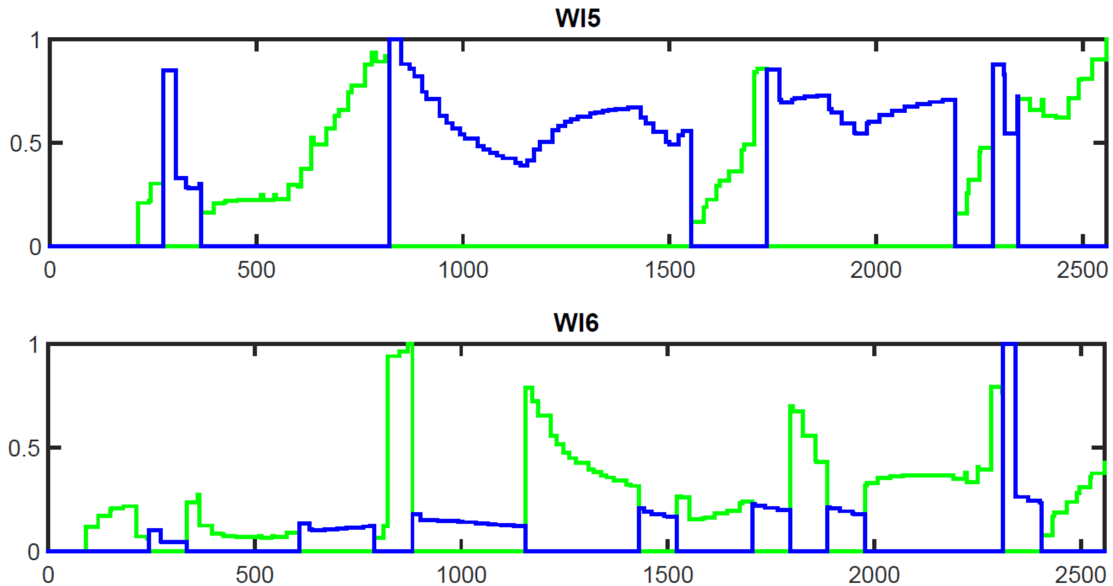


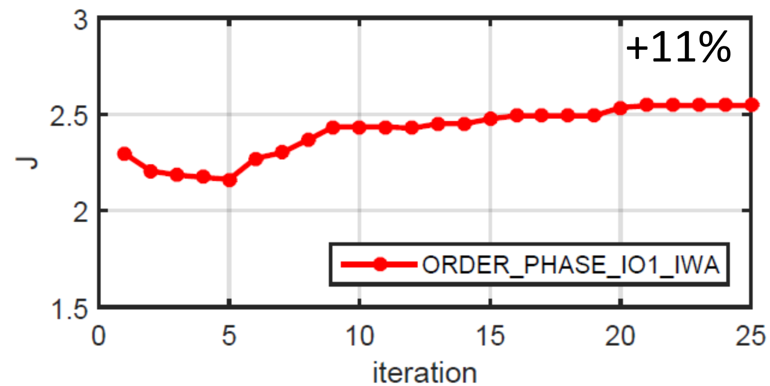
Robust joint order and WAG optimization





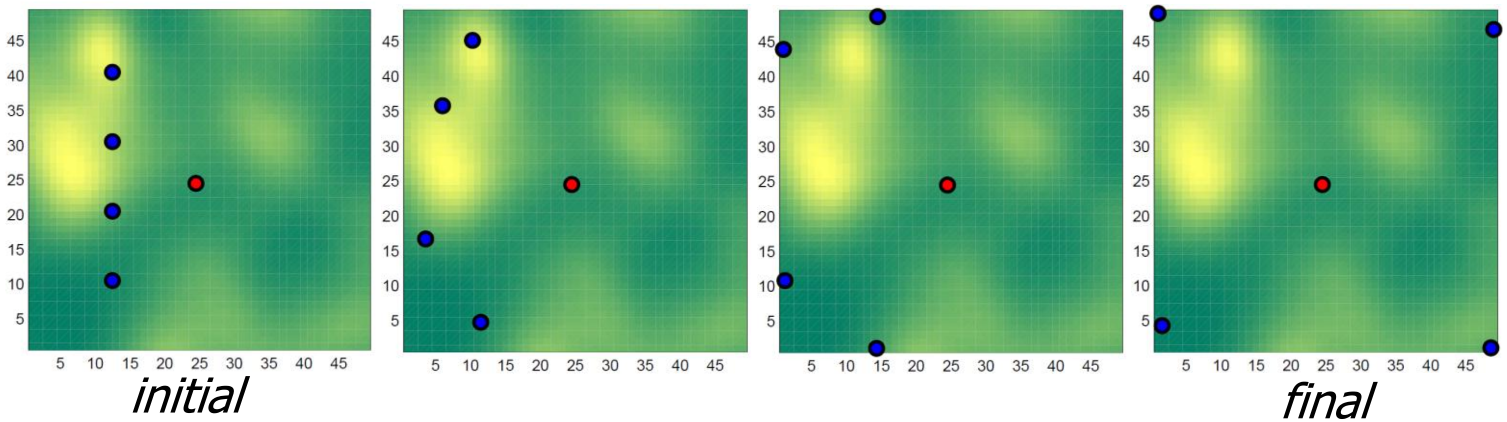
- Priority and phase controls
- 25 model realizations

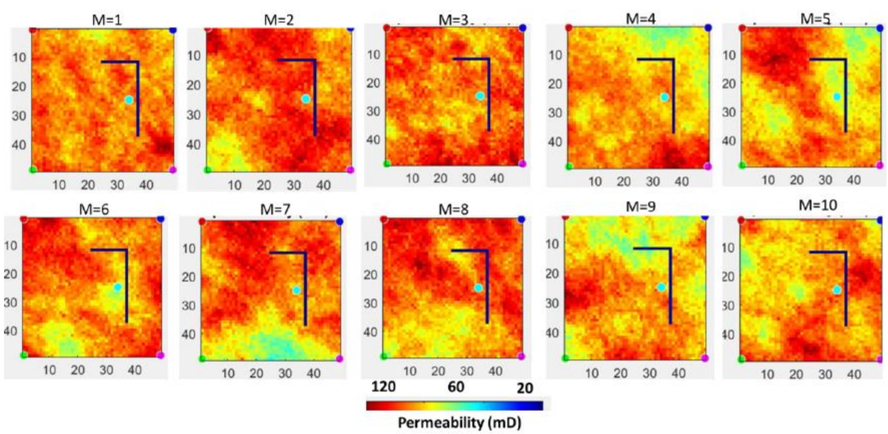


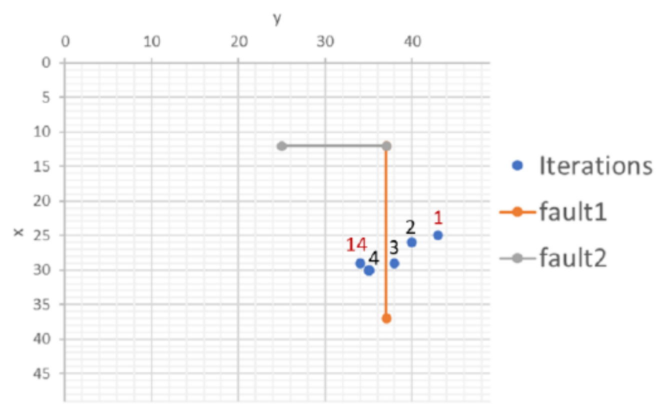


Feng, Leeuwenburgh, Hewson, Hanea, EAGE IOR2017.

Well placement

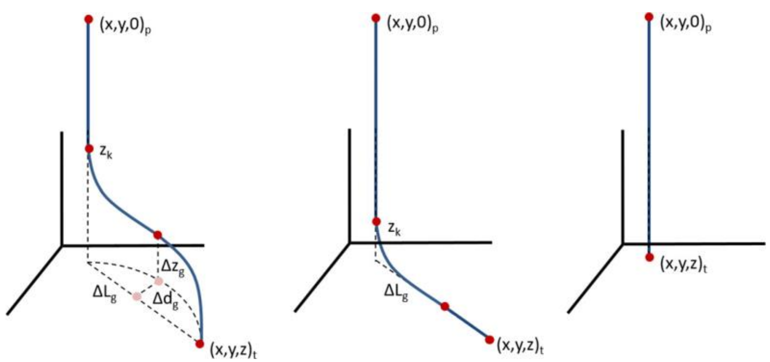


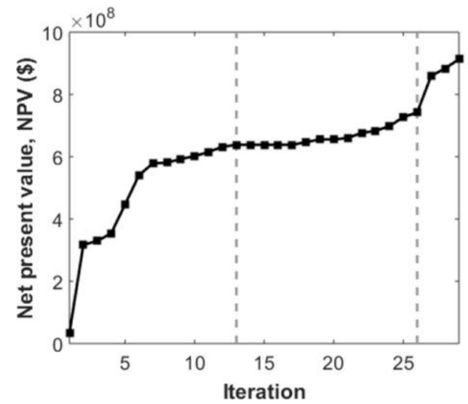


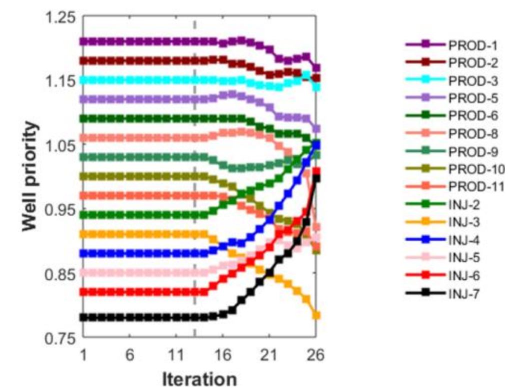


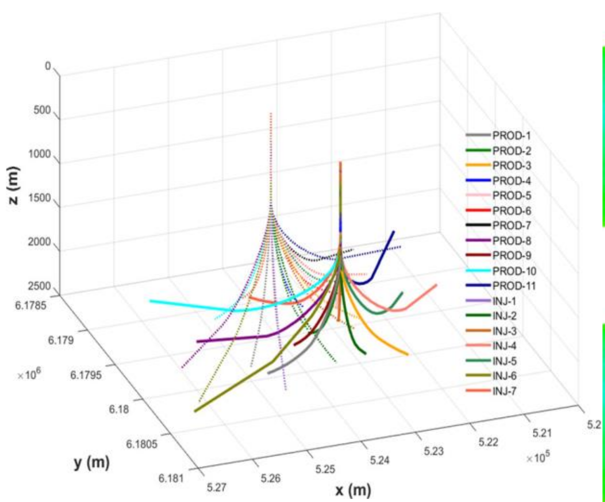
Well trajectory and drilling order

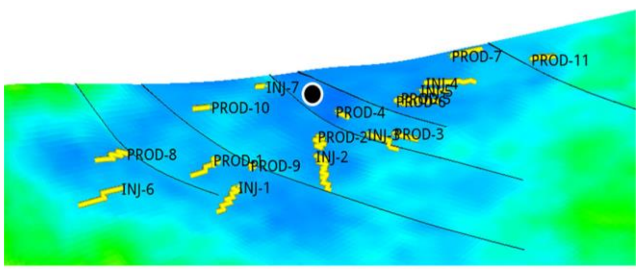
- Olympus benchmark case

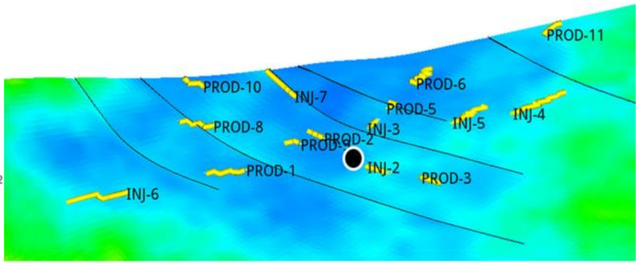












Barros, Chitu and Leeuwenburgh, 2020

Related work and trends

- Selection of realization subsets
- Alternative optimizer algorithms
- Use of various types of surrogate models
- Use as part of CLRM and VoI workflows
- Non-hydrocarbon subsurface applications

Conclusions

- Optimization workflows based on ensemble gradients have shown great flexibility, efficiency and effectiveness
  - Black box
  - Applicable also in some settings with non-continuous f, x
- Have been shown to work with
  - N_m, N_p ~ 10^1 – 10^2
  - n ~ 10^2 – 10^3
  - N_c ~ 10^0 - 10^2
- The ensemble-based gradient estimation approach is also attractive in settings with uncertainty and/or output constraints
- Applications to actual field cases have demonstrated value

Robust and Efficient Optimization Demonstrated on the OLYMPUS Field

Yuqing Chang, Geir Nævdal, Rolf Johan Lorentzen

September 7-8, 2021

IOR Centre Workshop on production optimization, value of information and decision-making

Introduction

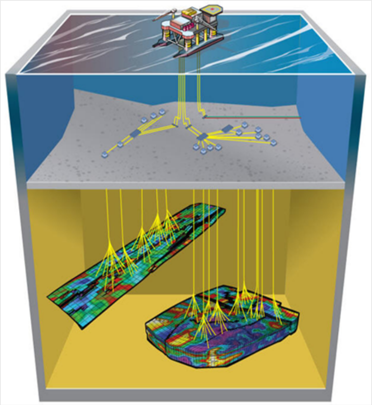
Optimization Problems

Optimization Algorithms

- Gradient-based Deterministic Algorithms: Newton's Method, Conjugate Gradient Method, Adjoint Method, etc.
- Gradient-free Stochastic Algorithms: Genetic Algorithm, Particle Swarm Optimization, etc.
- Stochastic Approximated-gradient Algorithms: EnOpt, SPSA, etc.

Production Optimization

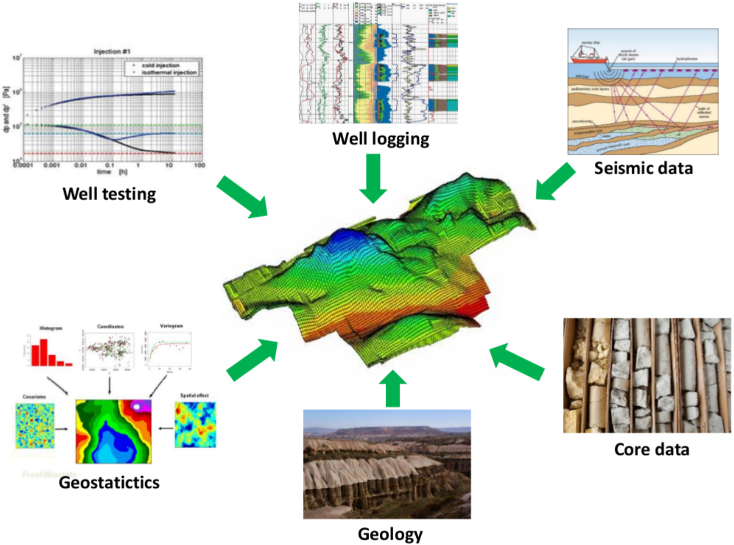
- Variables: locations, controls, pressures, etc.
- Objective functions
  - Net present value (NPV)
  - Cumulative oil production
  - Minimize cost and emission



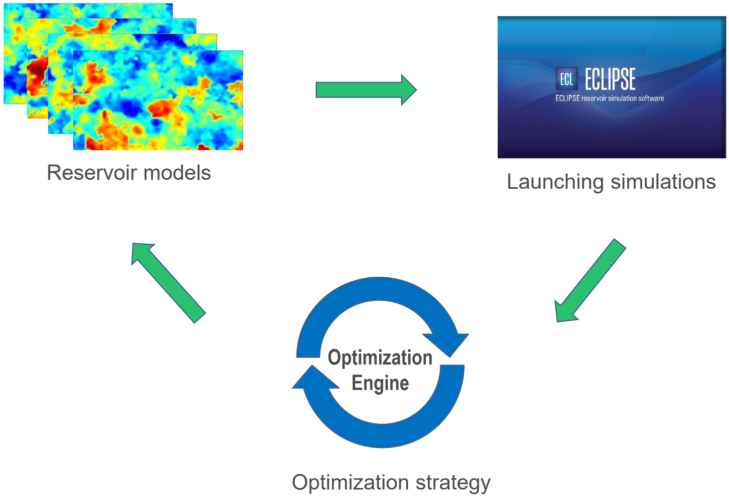
Source: Global Energy Experts.

The National IOR Centre of Norway

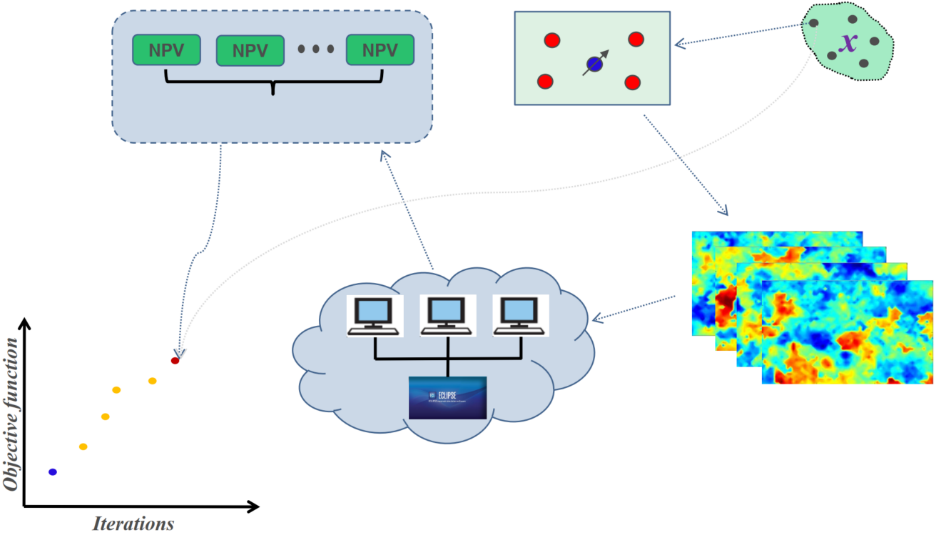
Reservoir Geological Uncertainty



Simulation-based Optimization

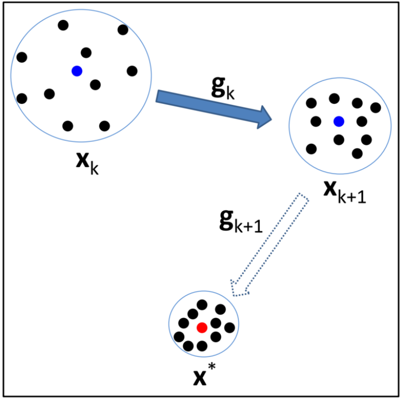


Optimization Under Uncertainty



Ensemble-based Optimization

Ensemble based optimization (EnOpt)



Ensemble based optimization (EnOpt)

- Pre-conditioned steepest ascend:

$$x_{k+1} = x_k + \eta_k C \nabla J_k$$

- Gradient approximation with geological uncertainty:

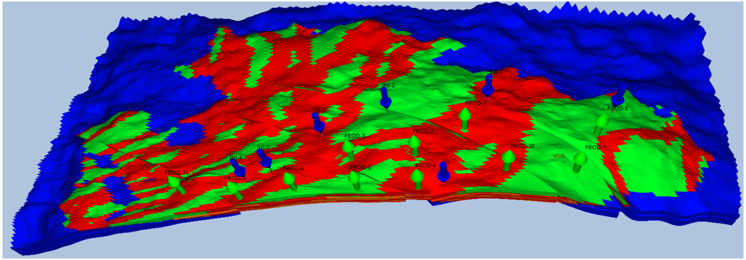
$$\nabla J_k \approx N^{-1} \sum_{i=1}^{N} [J(x_k^i, y^i) - J(x_k, y^i)][x_k^i - x_k]$$

- For more information we refer to:
  Chang et al. (2019), Stordal et al. (2016), Chen et al. (2009), Lorentzen et al. (2006)

OLYMPUS Field Case

The OLYMPUS field

- The OLYMPUS field[1] is prepared by TNO for the field development optimization challenges.
- Field size: 9 km $\times$ 3 km, with 50 m of thickness. The field has 6 minor faults, with one side bounded by a sealing fault.
- Reservoir model: 16 layers in total, with layer 8 as an impermeable shale layer.



[1] https://www.isapp2.com/optimization-challenge/problem-statement.html

Optimization problem

- Olympus field: 11 producers, 7 injectors
- 50 different reservoir models
- Find optimal production strategy
- Ensemble-based optimization
- Previous study (Chang et al., 2019): Optimizing producer shut-in time and injector pressure
- Now: Optimizing producers economic limits and injector pressure

Objective function

- Objective function:

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

- Revenue term:

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

Q_{op}, Q_{wp}, Q_{wi} - rates of oil, water production and water injection.
r_{op}, 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.

Constants for the field operation and NPV calculation

Table 1: Information used for NPV calculation and operation constraints for wells in Olympus Field

Contribution	Value (Metric Units)	Value (Field Units)
Oil price	283 ($\$/m^3$)	45 ($/bbl)
Water disposal cost	38 ($\$/m^3$)	6 ($/bbl)
Water injection cost	13 ($\$/m^3$)	2 ($/bbl)
Maximum plaform liquid production rate	14000 (m^3/day)	88000 (bbl/day)
Maximum well oil production rate	900 (m^3/day)	5700 (bbl/day)
Maximum well water injection rate	1600 (m^3/day)	10000 (bbl/day)
Injector BHP (bar)	235	
Producer BHP (bar)	150	
Annual discount factor	0.08	
End of the life cycle period (years)	20	

Uncertainty in the reservoir model

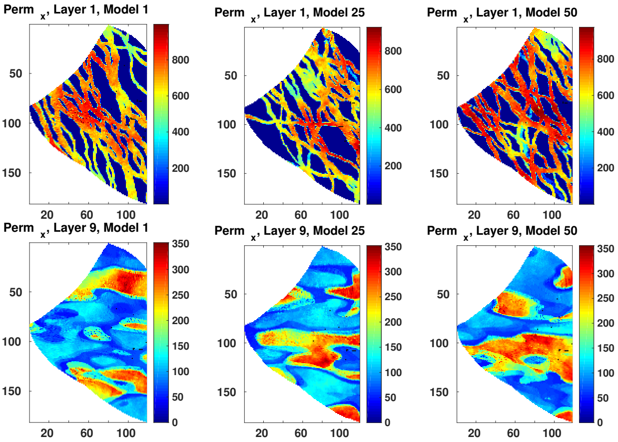


Figure: Uncertainty in permeability field at selected layers (Layer 1 and Layer 9) of selected geo-models #1, #25 and #50 (Unit: mD).

Optimizing well economic limits (WECON)

- EnOpt with backtracking is applied, $N = 50$.
- Control variables are well economic limits (WECON), and bottom hole pressures for injectors (INJBHP).
- The initial value for the stepsize is 0.1 and for the ensemble perturbation covariance is 0.01.
- WECON values are scaled to [0.05, 1], INJBHP values are scaled to [0,1].
- The objective function is scaled by 10^{-8}.

Optimizing WECON

Table 2: Summary of experiment results (Unit of J: 10^8 USD).

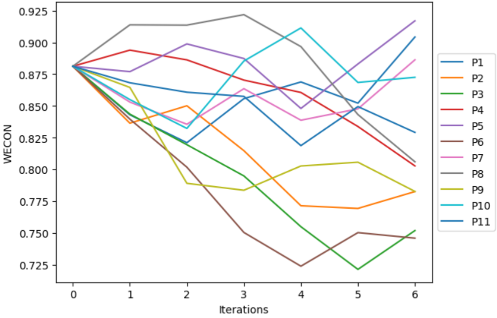
Runs	N_m	J_{init}	J_{max}	J_{max_all}	$N_{success\_iter}$	N_{total_iter}	N_{sim}
Run 1	50	14.88	15.06	15.06	3	13	1400
Run 2	50	14.88	15.12	15.12	4	14	1500
Run 3	25	14.96	15.44	**15.32**	6	10	550
Run 4	25	14.79	14.95	14.99	2	6	350

N_m: # geological models, J_{init}: average NPV – starting point, J_{max}: average NPV – optimal point, J_{max_all}: average NPV – over all models (optimal point), $N_{success\_iter}$: # successful iterations, N_{total_iter}: # total iterations (includes trial steps), N_{sim}: total number of simulations.

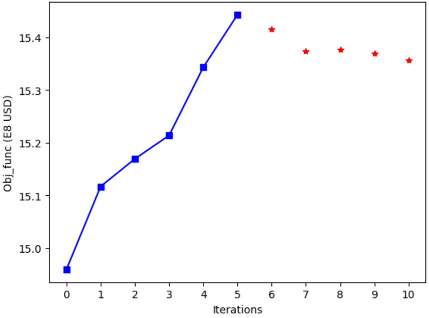
Table 3: Optimal values of WECON from Run 3.

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11
Optimal Values	0.90	0.78	0.75	0.80	0.92	0.74	0.89	0.80	0.78	0.87	0.83

Optimizing WECON



(a) WECON



(b) Objective function

Optimization results of Run 3. The red stars in the objective function plot represents the failed trial steps during the optimization.

Optimizing WECON and INJBHP

Table 4: Optimal injection pressure values (bar) of Chang et al. (2019).

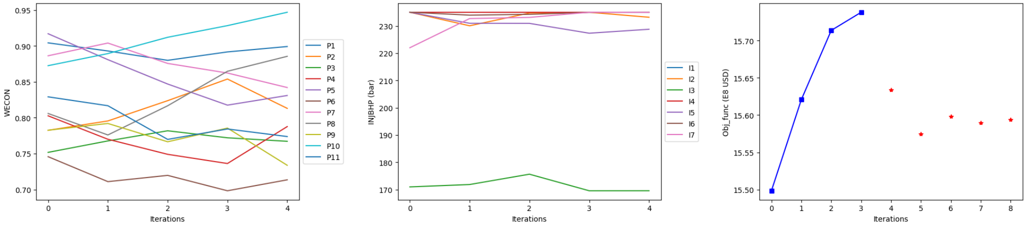
	I1	I2	I3	I4	I5	I6	I7
Optimal values	235	235	171	235	235	235	222

Table 5: Summary of experiment results (Unit of J: 10^8 USD).

Runs	Init. WECON	Init. INJBHP	N_m	J_{init}	J_{max}	$N_{success\_iter}$	N_{total_iter}	N_{sim}
R1	0.88	235	50	14.88	15.13	3	7	800
R2	0.88	Table 4	50	15.24	15.59	6	11	1200
R3	Table 3	Table 4	50	15.50	**15.74**	4	8	900

Note: The highest value achieved in our previous work Chang et al. (2019) was \$15.48 $\times$ 10^8.

Optimizing WECON and INJBHP



(a) WECON (b) INJBHP (c) Objective function

Optimization results of R3. The red stars in the objective function plot represents the failed trial steps during the optimization.

Summary and Discussions

- Well Economic Limits (WECON) for producers and well injection bottom hole pressure (INJBHP) gave higher NPV than shut-in time and INJBHP used prevously.
- EnOpt shows its efficiency when handling the geological uncertainty. The number of function evaluations used during the optimization is acceptable for situations when the computation resources are limited.
- The selection of sub-groups for representing the uncertainty may need further research.

Acknowledgments

The authors acknowledge

- The Research Council of Norway and the industry partners, ConocoPhillips Skandinavia AS, Aker BP ASA, Vår Energi AS, Equinor ASA, Neptune Energy Norge AS, Lundin Norway AS, Halliburton AS, Schlumberger Norge AS, Wintershall DEA, of The National IOR Centre of Norway for support.
- Schlumberger for providing academic software licenses for ECLIPSE.

References

Chang, Y., R. J. Lorentzen, G. Nævdal, and T. Feng, OLYMPUS optimization under geological uncertainty, *Computational Geosciences*, 2019.

Chen, Y., D. S. Oliver, and D. Zhang, Efficient ensemble-based closed-loop production optimization, *SPE Journal*, **14**(2), 634–645, 2009, sPE-112873-PA.

Lorentzen, R. J., A. M. Berg, G. Nævdal, and E. H. Vefring, A new approach for dynamic optimization of water flooding problems, in *SPE Intelligent Energy Conference and Exhibition*, Amsterdam, The Netherlands, 2006, paper SPE 99690.

Stordal, A. S., S. P. Szklarz, and O. Leeuwenburgh, A theoretical look at ensemble-based optimization in reservoir management, *Mathematical Geosciences*, **48**(4), 399–417, 2016.

Production optimization methodology and applications for EOR

Micheal B. Oguntola[1,2], *Rolf Lorentzen*[2]

1: University of Stavanger, 2: NORCE - Norwegian Research Center AS

September 8, 2021

Outline

Introduction

Problem faced with continuous water flooding (CWF)

- Sweep efficiency in:
  - highly heterogeneous reservoir
  - unfavorable mobility ratio (in heavy-oil reservoir), $\lambda = \frac{\lambda_o}{\lambda_w} > 1$
  - high interfacial tension (IFT).

Early Water Breakthrough ($\approx$ 94%) | High oil residual saturation

Viscous Fingering (due to Heavy Oil) | Reduced Oil Production

EOR classical approach:

Improve water flooding (WF) performance by:

1.) $0 < \lambda < 1$. 2.) Wetability alteration. 3.) Reduce IFT

in the oil-water system. EOR methods for this purpose are:

1. Polymer (p) 2. Smart water (s) 3. CO_2 (c).

Introduction (contd...)

Fixed slug size of EOR chemical injections (real field application)

- constant concentration or injection rate (given configuration of wells)
- improve oil recovery (only moderate)
- environmental and economic impact
- need to optimize the EOR control/ operating strategies.

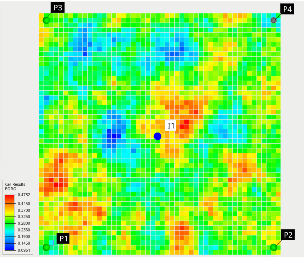
What is (and is not) in the literature ?

- general optimization procedure for EOR methods with no account for reservoir uncertainties.
- objective function is the net present value (NPV)[Economic value] with no account for back produced EOR
- value quantification and ranking of EOR method.

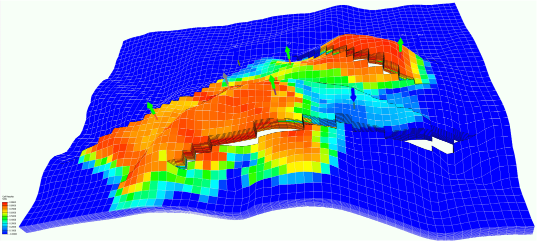
Introduction (contd...)

What we do:

- Perform general optimization procedure for EOR methods in the face of reservoir uncertainties (Test: Polymer, Smart water, and CO_2 flooding)
- Applications using: 2D 5Spot and 3D Reek fields
- Quantify the economic value of optimal control.



(a) 5Spot field



(b) Reek field

Model-based optimization for EOR methods

EOR control strategy, $\mathbf{u}^\mu$.

Two things to bear in mind:

1. economic value in the face of reservoir uncertainties.
   - ensemble of geological realizations, $\boldsymbol{\theta} = \{\theta_i\}_{j=1}^{N_e}$.
   - reservoir performance index, NPV:

   $$(\mathbf{u}^\mu, \theta_j) \xrightarrow{\text{Run sim.}} J(\mathbf{u}^\mu, \theta_j) = \sum_{i=1}^{N_t} \frac{R_j(t_i)}{(1+d_\tau)^{\frac{t_i}{\tau}}}, \quad \forall j = 1, 2, ..., N_e,$$

   where

   $$R_j(t_i) = r_o Q_{o,i}(\mathbf{u}^\mu, \theta_j) + r_g Q_{g,i}(\mathbf{u}^\mu, \theta_j) - \Big[r_{wi} Q_{w,i}(\mathbf{u}^\mu, \theta_j) + r_{wp} Q_{wp,i}(\mathbf{u}^\mu, \theta_j) + r_{ei}^\mu Q_{ei,i}(\mathbf{u}^\mu, \theta_j) + r_{ep}^\mu Q_{ep,i}(\mathbf{u}^\mu, \theta_j) \Big]$$

   - Q_o, Q_g, Q_w, Q_{wp}, Q_{ei}, and Q_{ep} are primary variables obtained from solving fluid-flow equations (OPM-Flow simulator)

2. environmental impact (Back EOR or water produced).

EOR method (μ=p, s, c)

Control vector or strategy, $\mathbf{u}^{\mu}$ (for a given well configuration) includes:

- water injection rate/ bottom hole pressure (injectors)
- EOR concentration/ injection rate (injectors)
- oil production rate/ bottom hole pressure (producers).
- e.g. $\mathbf{u}^{\mathrm{p}}$ =[(oil rate, water rate, polymer conc., bph)$_1, \ldots,$]

$N^{\mu}-$dimensional constrained optimization problem

Let $\mathcal{D} \subset \mathbb{R}^{N^{\mu}}$ be the domain of feasible control vectors $\mathbf{u}^{\mu} = \{u_i\}_{i=1}^{N^{\mu}}$, with $N^{\mu} = N_{well} \times N_t$ for an oil reservoir with $\theta = \{\theta_j\}_{j=1}^{N_e}$.

$$\max_{\mathbf{u}^{\mu} \in \mathcal{D}} \left[J_{\boldsymbol{\theta}}(\mathbf{u}^{\mu}) := J(\mathbf{u}^{\mu}) := \frac{1}{N_e} \sum_{j=1}^{N_e} J(\mathbf{u}^{\mu}, \theta_j) \right],$$

$$s.t, \quad u_i^{\mathrm{low}} \leq u_i \leq u_i^{\mathrm{upp}} \text{ and } \sum_{r=1}^{N_c} u_r \leq C_{\mathrm{total}}$$

Solution method

Optimization procedure (Oguntola and Lorentzen, 2020)

- select initial guess, $\mathbf{u}_0^\mu$ based on experimental fact
- updating scheme (Preconditioned GAM):

$$\mathbf{u}_{k+1}^\mu = \mathbf{u}_k^\mu + \frac{1}{\beta_k}\frac{\mathbf{C}_{\mathbf{u}^\mu}^k \mathbf{G}_k^T}{||\mathbf{C}_{\mathbf{u}^\mu}^k \mathbf{G}_k^T||_\infty}, \qquad \forall k = 0, 1, 2, ...,$$

- non-correlation (controls at different wells) and smooth variation (controls at each well) with time; $\mathbf{C}_{\mathbf{u}^\mu}^k$.
- initial covariance matrix, $\mathbf{C}_{\mathbf{u}^\mu}^0$ using stationary AR(1) model:

$$\mathrm{Cov}(u^m[t], u^m[t+h]) = \sigma_m^2 \rho^h \left(\frac{1}{1-\rho^2}\right), \qquad \forall\ h \in [0, N_t - t],$$

- Adaptive scheme (Stordal et al. 2016): $\mathbf{C}_{\mathbf{u}^\mu}^k, k \neq 0$.

Solution method (contd...)

Preconditioned approximate gradient, $\mathbf{C}^k_{\mathbf{u}^\mu}\mathbf{G}^T_k$

EnOpt approach (Chen et al. 2009): At *kth* iteration, $\mathbf{u}^\mu_k$ and $\mathbf{C}^k_{\mathbf{u}^\mu}$ (known)

- sample, $\mathbf{u}_{k,j} \sim \mathcal{N}(\mathbf{u}^\mu_k, \mathbf{C}^k_{\mathbf{u}^\mu}),\ j = 1, 2, ..., N \geq N_e,$
- random coupling (1-1 with geology): $(\mathbf{u}_{k,j}, \theta_j),\ j = 1, 2, ..., N,$

$$(\mathbf{u}_{k,j}, \theta_j) \xrightarrow{\text{Run sim.}} J(\mathbf{u}_{k,j}, \theta_j),\ j = 1, 2, ..., N.$$

Cross-covariance between $\mathbf{u}^\mu_k$ and $J(\mathbf{u}^\mu_k)$:

$$\mathbf{C}^k_{\mathbf{u}^\mu, J(\mathbf{u}^\mu)} \approx \frac{1}{N-1}\sum_{j=1}^{N}(\mathbf{u}_{k,j} - \mathbf{u}^\mu_k)\Big(J(\mathbf{u}_{k,j}, \theta_j) - J(\mathbf{u}^\mu_k, \theta_j)\Big).$$

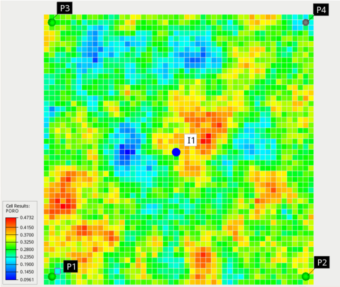
By 1st-order Taylor series expansion on $J(\mathbf{u}^\mu)$ about $\mathbf{u}^\mu_k$:

$$\mathbf{C}^k_{\mathbf{u}^\mu, J(\mathbf{u}^\mu)} \approx \mathbf{C}^k_{\mathbf{u}^\mu}\mathbf{G}^T_k.$$

Case1: The 5Spot field

3-phase
flow (oil, water and gas) reservoir.
Dimension, $50 \times 50, \Delta x = \Delta y = 100$ m

- 1 injector (bhp = 500bars)
  & 4 producers (bhp = 150bars).
- Light-oil reservoir.
- pySCAL generates:
  - relperm input curves
  - Corey parameterization
- Simulation period: 1500days,
  time step: 30days.
- Fair comparison: Mass (per unit time) equivalence for EOR injection (density of $C0_2 = 1.815 \text{kg}/\text{m}^3$)



Controls:

μ=p:{Polymer conc., water rate, oil rate}$\rightarrow \{u_i\}_{i=1}^{300}$

μ=s:{Salt conc., water rate, oil rate}$\rightarrow \{u_i\}_{i=1}^{300}$

μ=c:{CO_2 injection rate, oil rate}$\rightarrow \{u_i\}_{i=1}^{250}$

Case 1: 5Spot field

Optimization parameters

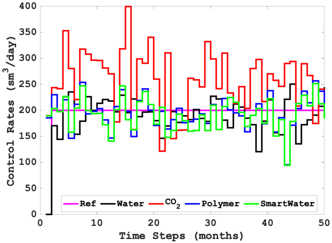
$\beta_0^{-1} = 0.3, \sigma_m^2 = 0.01, \forall m = 1, 2, .., \rho = 0.5$, and $N = 10$ perturbation.

Economic parameters

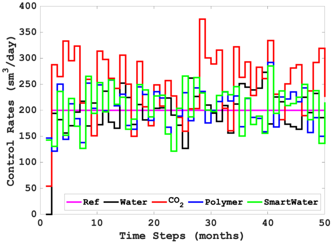
Parameter	Value	Unit
Oil price	500	USD/sm^3
Price of gas	0.5	USD/sm^3
Cost of polymer inj/prod	2.5/0.5	USD/kg
Cost of C0$_2$ inj/prod	1.2/0.1	USD/sm^3
Cost of water inj/prod	30/30	USD/sm^3
Cost of Smart water inj/prod	2.5/0.5	USD/kg
Annual discount rate	0.1	–

- Optimization of water flooding (same setup).

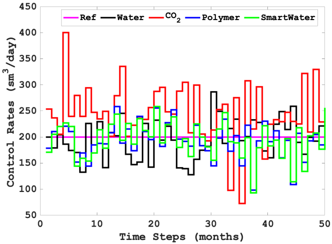
Optimal controls for producers (5Spot field)



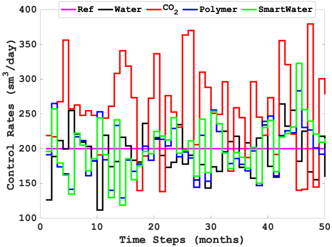
(a) P1



(b) P2

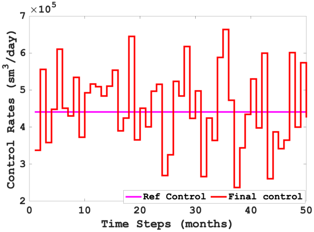


(c) P3

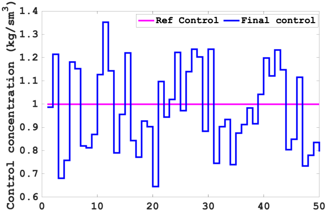


(d) P4

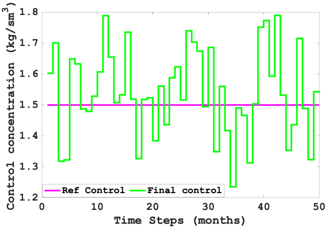
Optimal controls for EOR-injection (5Spot field)



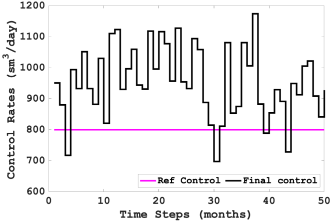
(a) CO_2 injection rate



(b) Polymer injection rate

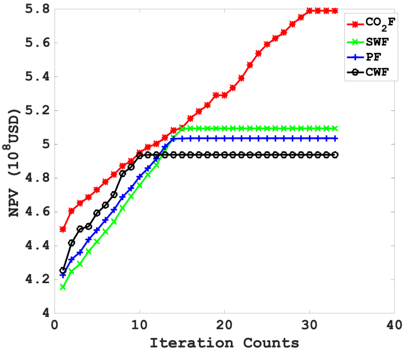


(c) Smart water injection rate

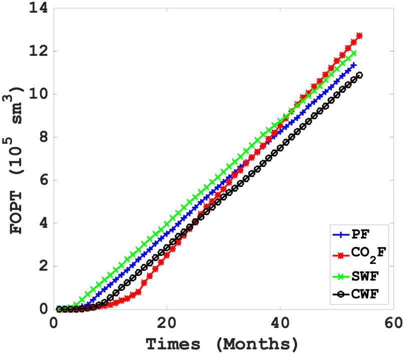


(d) Water injection rate

Value quantification (5Spot field)



(a) NPV variation



(b) Field oil production

Case 2: The Reek field

3-zones, 6-faults (highly heterogeneous) 3D, 3-phase flow reservoir.
Dimension, $40 \times 64 \times 14$.

- 3 injector & 5 producers.
- pySCAL generates:
  - saturation maps
  - solvent and gas rel perm tables
- Light-oil reservoir
- Fifty geological descriptions (porosity, permeability, oil-water contacts, facies, transmissibility across faults)
- Simulation period: 1110days, time step: 30days

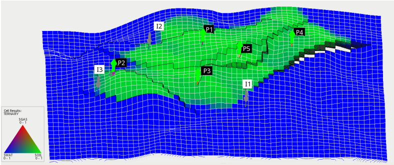


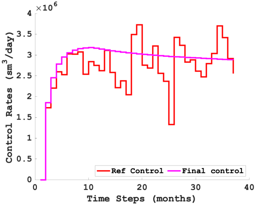
Figure 5: Initial saturation map

Controls:

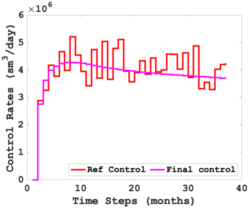
p:{Polymer conc., water rate, oil rate} $\rightarrow \{u_i\}_{i=1}^{407}$
s:{Salt conc., water rate, oil rate} $\rightarrow \{u_i\}_{i=1}^{407}$
c:{CO_2 injection rate, oil rate} $\rightarrow \{u_i\}_{i=1}^{296}$

Optimal controls for injectors (Reek field)

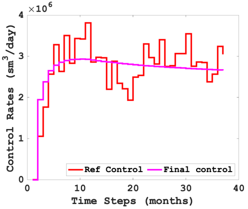
CO_2 flooding:



(a) I1

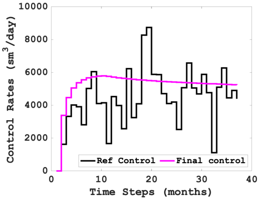


(b) I2

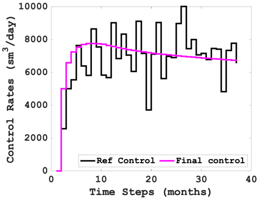


(c) I3

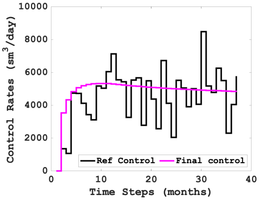
Water flooding:



(d) I1



(e) I2



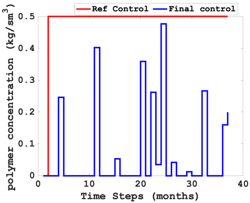
(f) I3

University of Stavanger

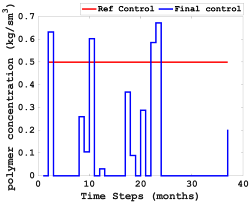
NORCE

Optimal controls for injectors (Reek field)

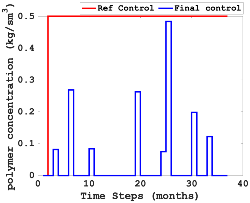
Polymer flooding:



(a) I1

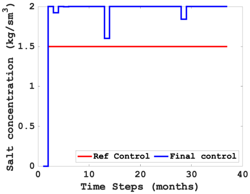


(b) I2

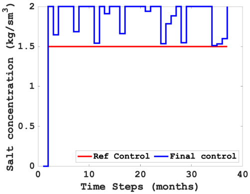


(c) I3

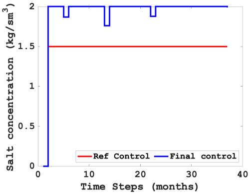
Smartwater flooding:



(d) I1

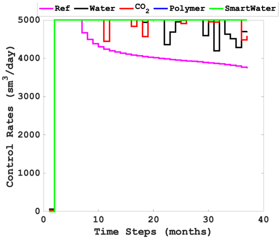


(e) I2

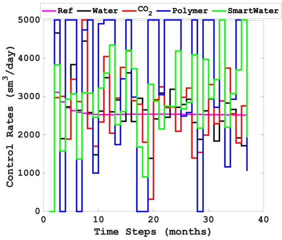


(f) I3

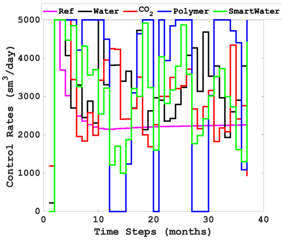
Optimal controls for producers (Reek field)



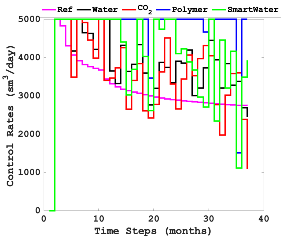
(a) P1



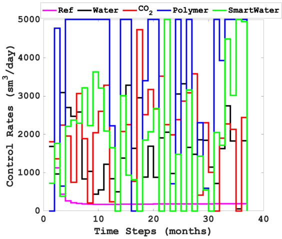
(b) P2



(c) P3



(d) P4



(e) P5

Value quantification (Reek field)

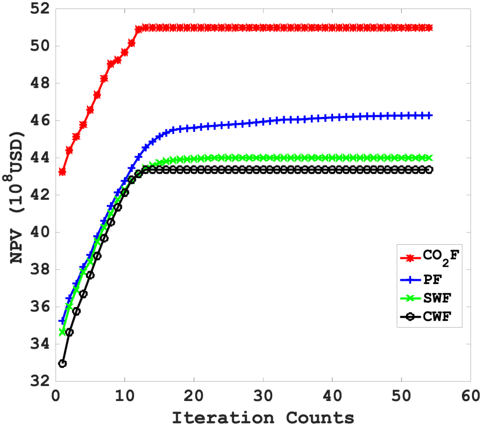
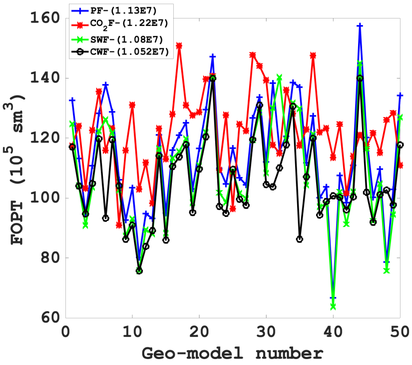
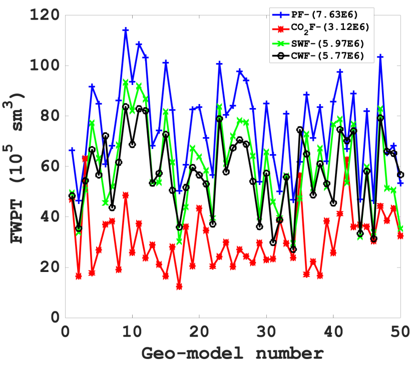


Figure 9: NPV variation

Value quantification (Reek field)



(a) Field oil production



(b) Field water production

Conclusion

- EOR optimization workflow with appropriate objective and applications
- Quantification of value of EOR methods
- Continuous CO_2 flooding performs better than others
- Recommendation:
  - Optimize different ionic concentrations than salt in smart water problem.
  - Sensitivity of uncertain parameters to different control strategies leading to high oil production.
  - Consider optimization problems with combined EOR methods.

Acknowledgments

We thank

- The Research Council of Norway and the industry partners, ConocoPhillips Skandinavia AS, Aker BP ASA, Vår Energi AS, Equinor Energy ASA, Neptune Energy Norge AS, Lundin Energy Norway AS, Halliburton AS, Schlumberger Norge AS, Wintershall Dea Norge AS, of The National IOR Centre of Norway for the support.
- Equinor ASA for sharing the Reek field data

Reference

[1] Oguntola, M., & Lorentzen, R. (2020, September). On the Robust Value Quantification of Polymer EOR Injection Strategies for Better Decision Making. In ECMOR XVII (Vol. 2020, No. 1, pp. 1-25). European Association of Geoscientists & Engineers

[2] Chen, Y., Oliver, D. S., & Zhang, D. (2009). Efficient ensemble-based closed-loop production optimization. SPE Journal, 14(04), 634-645.

[3] Stordal, A. S., Szklarz, S. P., & Leeuwenburgh, O. (2016). A theoretical look at ensemble-based optimization in reservoir management. Mathematical Geosciences, 48(4), 399-417.

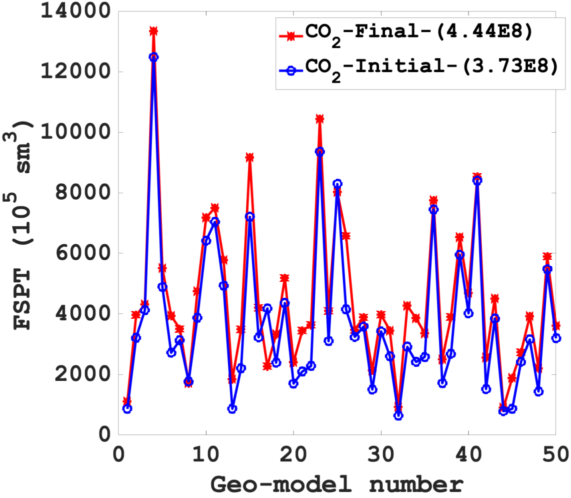


Figure 11: CO_2 production

Uncertainty centric workflows - Value and Challenges

In the context of the overall digital agenda

Thierry Laupretre

8 September 2021

Aker BP's digital vision is to fully transform core end-to-end processes

END TO END PROCESSES

- Integrated design & field development
- Well construction & Intervention
- Subsurface interpretation & modelling
- Maintenance & integrity
- Production optimization & energy management

No cyber-attack having significant effect on business or operations.

Aker BP working integrated and seamlessly in a fully digital and Cloud native eco-system.

All strategic and operational data is made available to the user at the right quality and time.

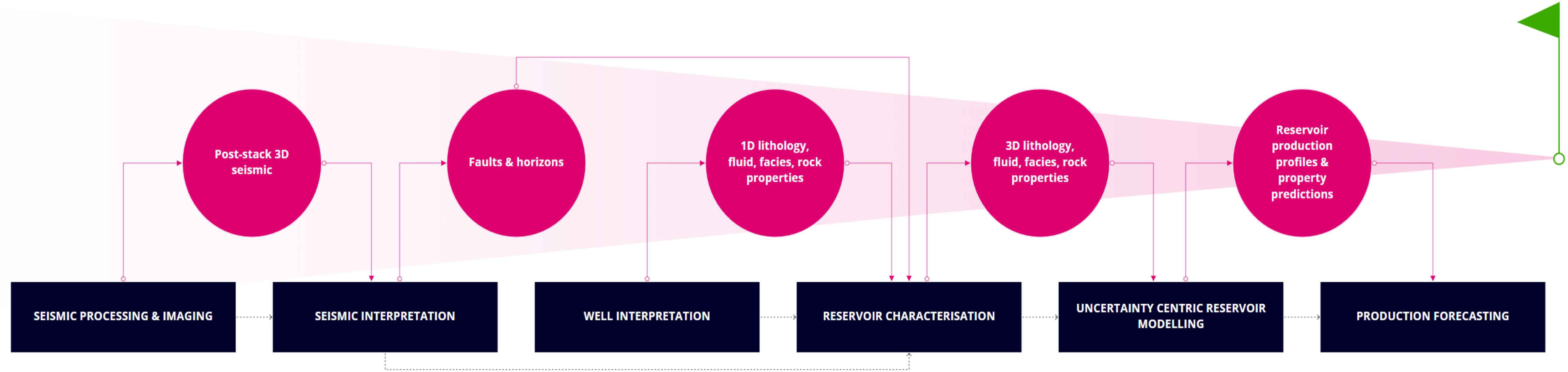
Agile workforce capable of quickly adapting and utilizing digital solutions.

AkerBP

SUBSURFACE INTERPRETATION AND MODELLING (SIM)

High level E2E-process and main value targeted by EurekaX

Goal:
Increase speed and quality of business decisions via evergreen range of valid interpretations and reservoir models



Targetted improvements	
• Optimized seismic images allowing more detailed interpretations • Increased automation • Improved asset involvement and discipline integration • Quick-look ML products; ML-driven evergreen interpretations • Quantified uncertainty of products	• Consistent process across assets • Improved dataflow • Increased automation • Quantified impact of uncertainties

ResX in Aker BP

- Collaboration agreement with Resoptima entered mid-2018
  - Support resources for ResX implementation
  - Collaborative effort on developing IRMA
- Testing and progressive application in all operated areas
- New agreements with Resoptima from 2021

Area	Start date / Project	Purpose
NOAKA	2017 / Frøy	Redevelopment evaluation
Skarv	2018 / Ærfugl	Well planning
Ula	2019 / Tambar	Infill evaluation
Ivar Aasen	2019 / Ivar Aasen	Testing of ResX for IA
Alvheim	2019 / Vilje 2021 / Bøyla	Testing and reserves support Infill evaluation
Valhall	2019 / Hod 2020 / Valhall	Hod PDO + well planning Valhall new platform evaluation

2020 Retrospective

Main Learnings

- Perceived **risk** in achieving results.
  - Resources partly allocated
  - Performed on the side of traditional workflows
- ResX: powerful but **demanding workflow**.
  - Only few teams get in control of their workflows, building independence from support
  - Lack of learning across projects
  - New projects or major updates needing tight support
- **Difficulties in QC'ing, and in learning** from ensemble updates
- **Needs for QC of uncertainty centric approach** expanded as compared to QC of deterministic models
- Recognized **value of discipline integration** and **increased decision robustness** in projects that have been appropriately resourced

Main actions

- **Competence development** in Central team
  - Testing to understand implications of using Adaptive Pluri-Gaussian and Kalman smoother algorithms
  - Tight follow-up and learnings from multiple projects
- **Sprints**
  - Revised set-up of new ResX projects with 3week-sprints
  - Training + de-risking
- **IRMA development acceleration**
  - User feedback and testing of new IRMA functionalities
  - Ideation process and collaboration with Resoptima for quick implementation of interrogation tools in IRMA lab

Value of uncertainty centric workflows to date

Better Project Decisions
- Better definition of outcome distribution, thus project value
- Saved cost by cancelling a well (initially identified in deterministic model)
- Approved project based on plan optimization across range of outcomes

Better plans
- Moving wells in more robust locations
- Contingency plans for upsides and downsides
- Better definition and justification of data needs
- Optimized reservoir management

Speed and Automation
- Quick updates post drilling via Robust set-up of workflows and team integration
- Clear when to review geological concept and HM levers
- Automated screening of opportunities

Better Safety
- Better inputs for detailed well planning

- **Main drivers**:
  - Enhanced work integration between disciplines
  - Recognizing uncertainty both in data and interpretations
  - Actually handling all data and having uncertainty studies constrained by data
  - Workflow skills and automated data conditioning

Challenge to research community

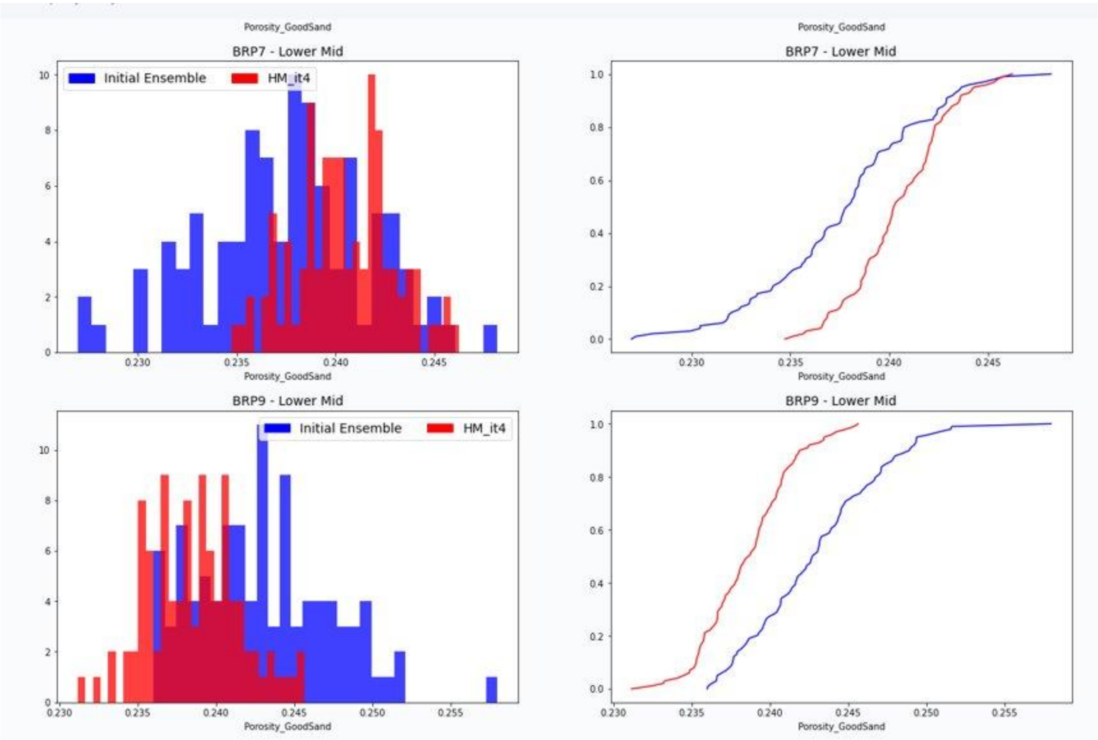
Simplify QC and learning process from ensembles

- Much R&D work towards integration of more data types and improving accuracy of methodology
  - Made it a powerful technique
  - Further activities planned to handle alternative scenarios/concepts

- But “implementation challenges” to handle current products of existing workflows
  - Much easier interrogation of ensembles achieved by collaboration with Resoptima and prototyping of apps to help learn from HM iterations
  - Need for further standardization and simplification of analysis for QC of inputs and effective use of outputs, e.g:
    - How to understand key drivers in changes?
    - How to QC fitness of inputs to methodology?
    - How to assess true diversity of outputs?
    - …

Example of App in IRMA

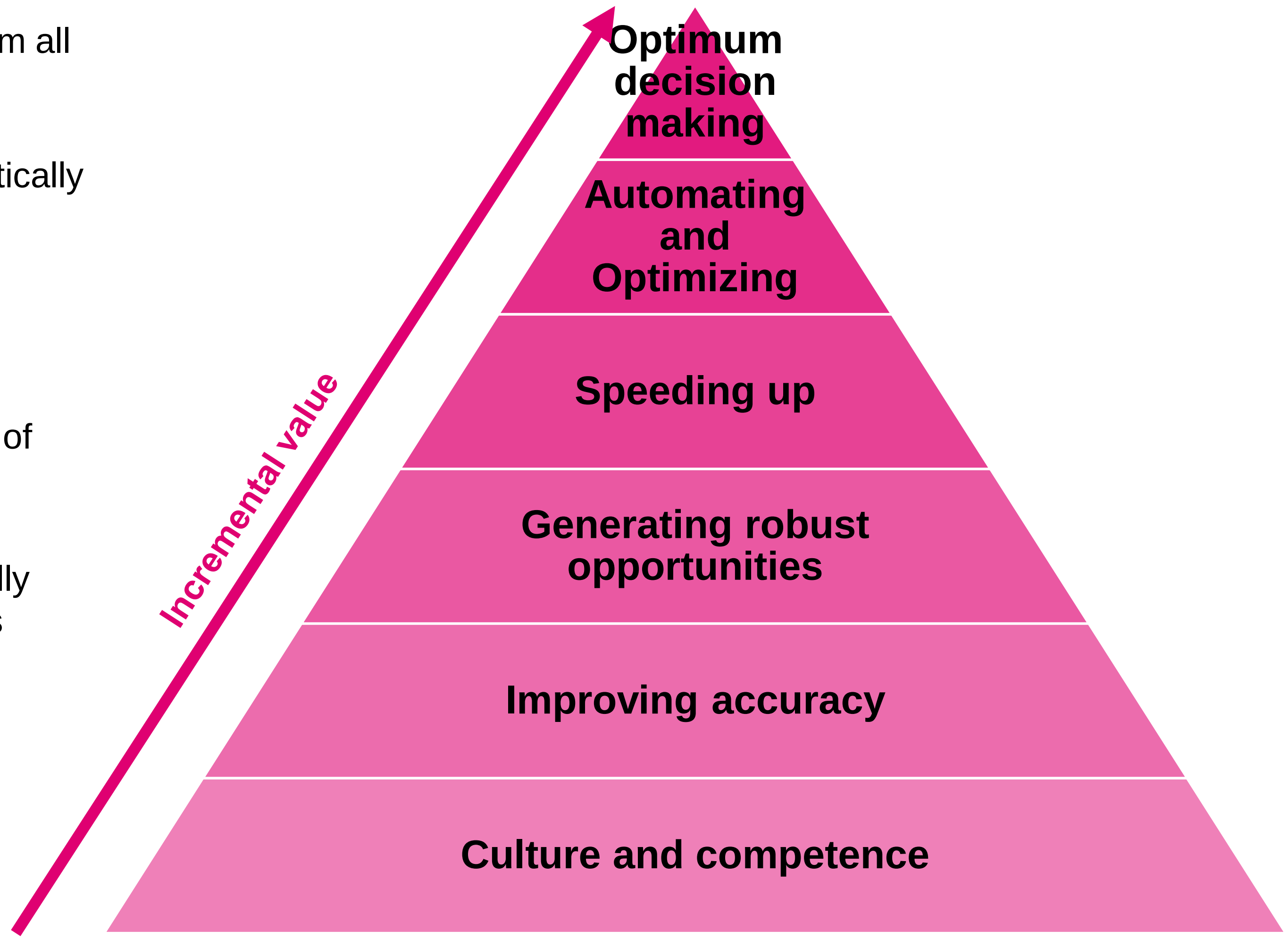
Comparing aggregated properties pre and post HM in localization regions



Summary and link to Strategy

Uncertainty centric workflows are core to fully utilizing data and reaching digitalization ambitions

- Models are where we integrate data/information/knowledge from all disciplines to allow quality decisions
- Uncertainty centric modelling enables to extract more systematically the value of this data:
  - By handling and honoring all the data
  - By allowing determination of robust plans
  - By speeding up updates through workflows/automation
- Uncertainty centric modelling also allows a better identification of further data acquisition needs and determination of their value
- Efforts are still needed to process ensembles of models and fully learn from the data conditioning process and exploit the results



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IOR Centre Workshop 2021

Monte Carlo Simulation plus Machine Learning Methods for Value-of-Information Calculations

Jo Eidsvik

Jo.Eidsvik@ntnu.no

Thanks to Geet Dutta, Tapan Mukerji, Debarun Bhattacharjya, Susan Anyosa, Scott Bunting, Anouar Romdhane, Per Bergmo.

CGF SFI Centre for Geophysical Forecasting

Key questions:

- Decisions about infill drilling or injection / production strategies.
  - Uncertainty, heterogeneties and complex dependencies make this choice difficult.

- Data gathering decisions about time-lapse seismic data.
  - Which kind of data are likely to be valuable? When should data be gathered? How much data is enough?

Key questions:

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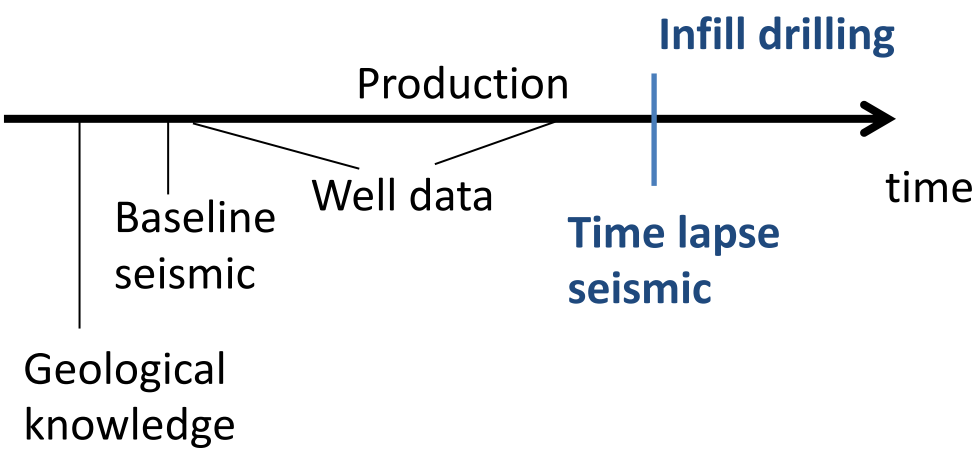
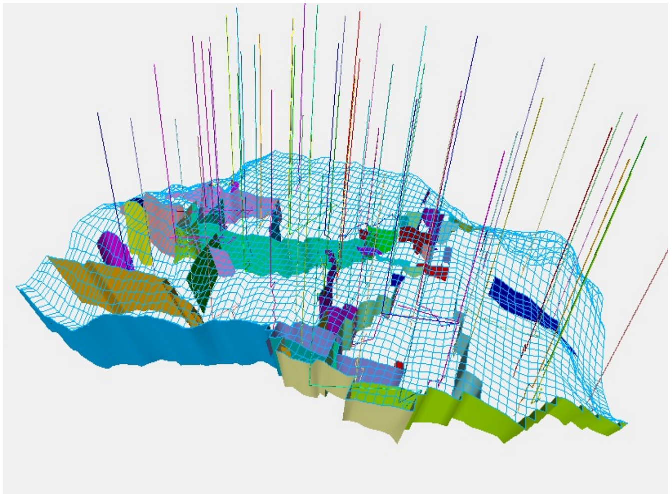


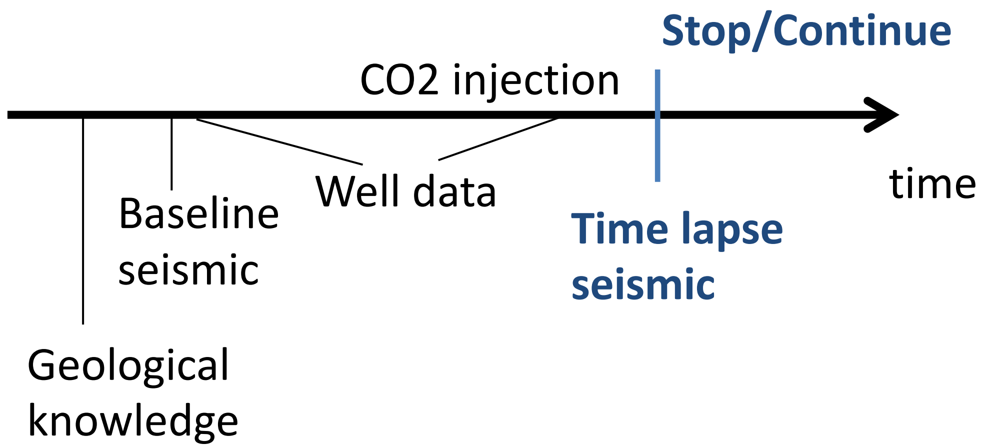


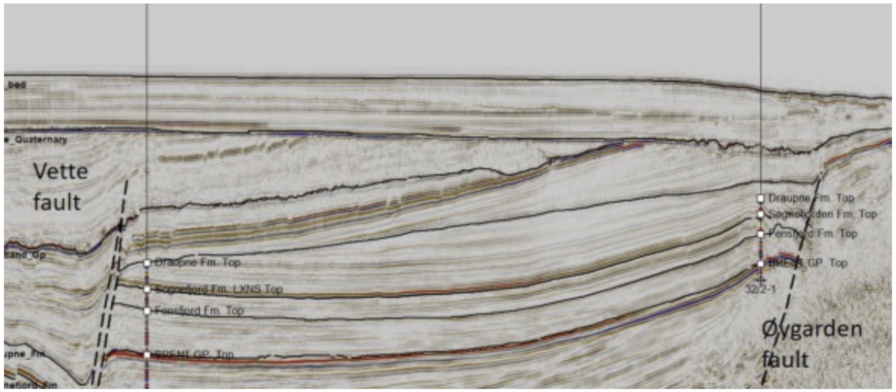
Wells drilled at the Gullfaks field, North Sea.

Key questions:

- Decisions about infill drilling or injection / production strategies.
  - Uncertainty, heterogeneties and complex dependencies make this choice difficult.

- Data gathering decisions about time-lapse seismic data.
  - Which kind of data are likely to be valuable? When should data be gathered? How much data is enough?





Smeaheia CO_2 storage site.

Notation

- Uncertain reservoir variables:
  - porosity, permeability, saturation, pressure, fault properties, elastic properties

  (some static, some dynamic)

$$\boldsymbol{x} = (x_1, \ldots, x_n)$$

Prior model: $p(\boldsymbol{x})$

- New information would include time-lapse seismic data:
  - stacked acoustic impedance : (AI)
  - pre-stack processing of AVO attributes : (R0,G)

$$\boldsymbol{y} = (y_1, \ldots, y_m)$$

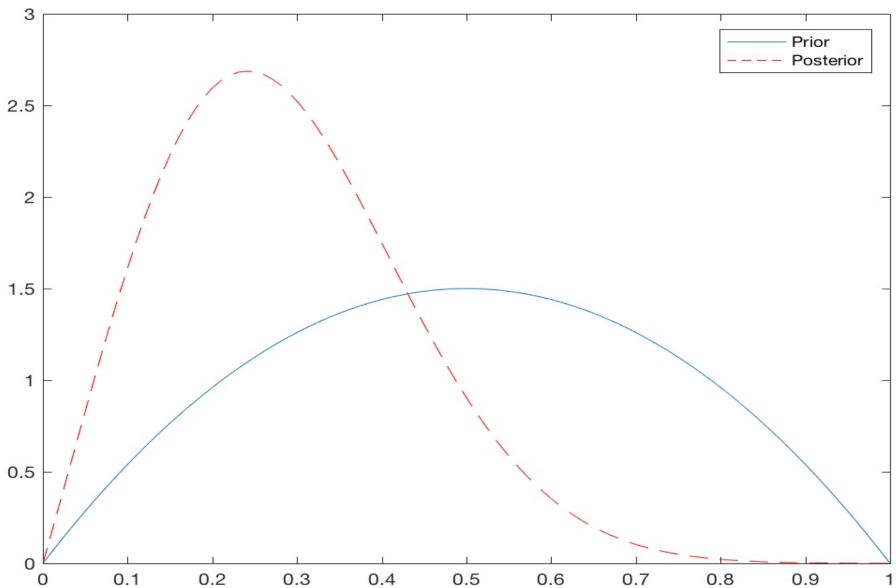
Likelihood model:

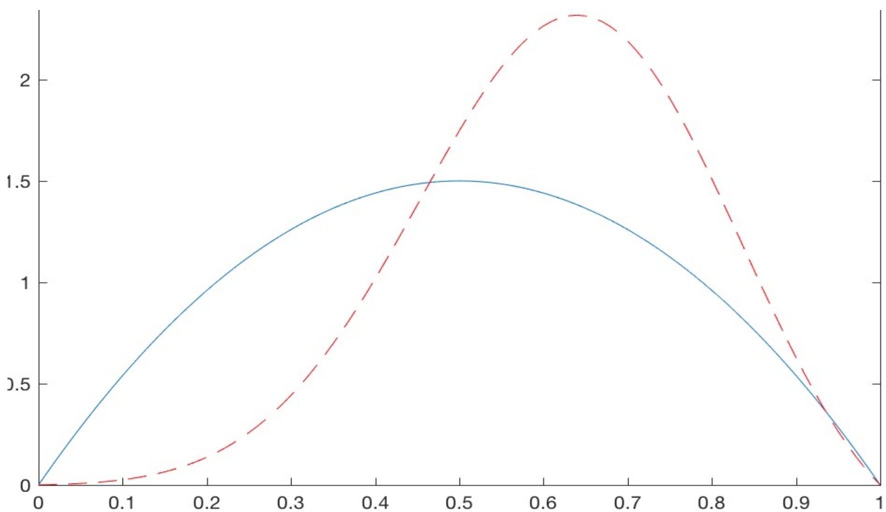
$$p(\boldsymbol{y} \mid \boldsymbol{x})$$

Bayesian setting:

$$p(\boldsymbol{x} \mid \boldsymbol{y}) = \frac{p(\boldsymbol{y} \mid \boldsymbol{x})\, p(\boldsymbol{x})}{p(\boldsymbol{y})},$$

Bayesian updating





$$p(\boldsymbol{x})$$

$$p(\boldsymbol{x} \mid \boldsymbol{y})$$

- What data is valuable?
- Study the **expected effect of data,** before it is collected.
- We gather data not only to reduce uncertainty, but to make better **decisions**.

Decision analysis

- Uncertain reservoir variables: $\boldsymbol{x} = \left(x_1, \ldots, x_n \right)$

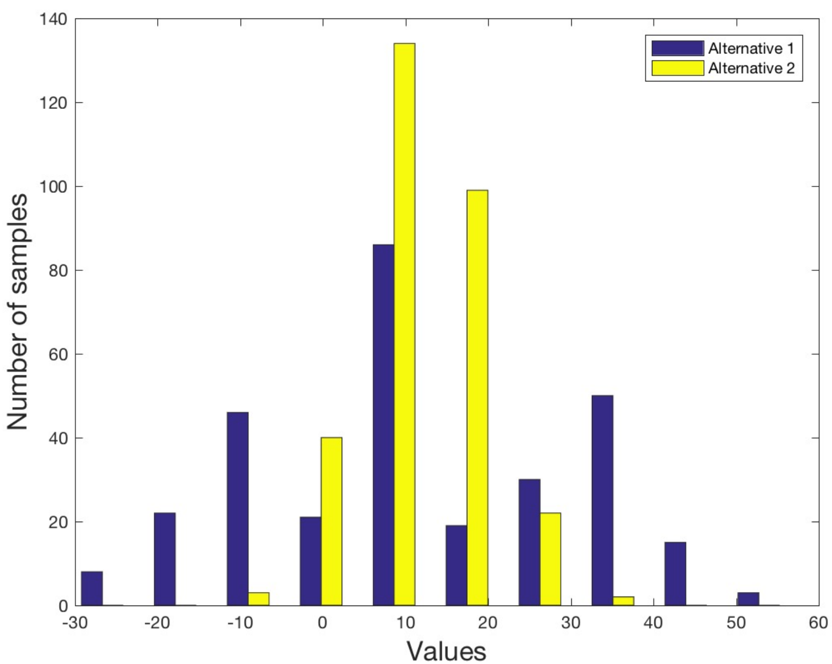
- Infill drilling alternatives (Where? How?) $\boldsymbol{a} = \left(a_1, \ldots, a_N \right)$
- Value function is revenues of production, subtracted costs. $v\left(\boldsymbol{x}, \boldsymbol{a} \right)$

- Risk neutral decision maker will **maximize expected value**:

$$PV = \max_{\boldsymbol{a} \in A} \left\{ E\left(v(\boldsymbol{x}, \boldsymbol{a}) \right) \right\},$$

Illustration of values

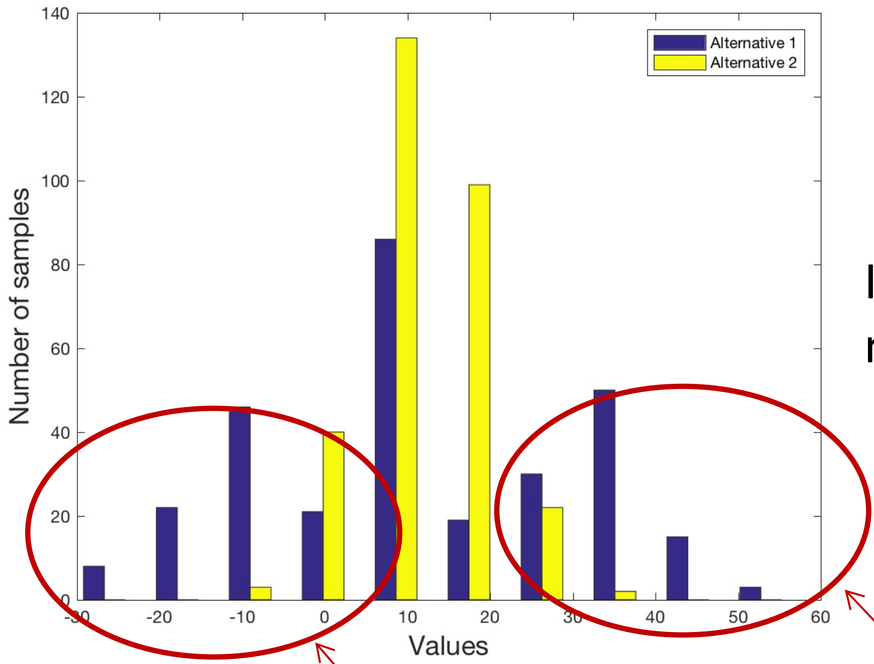
Conduct infill drilling?
- Decision is difficult because of uncertainty in reservoir properties, and hence in values.



Infill drilling (Alternative 1, blue) can give more value, but can also mean loss.

$$v(\boldsymbol{x}, \boldsymbol{a})$$

Illustration of values and data influence



Infill drilling (Alternative 1) can give more value, but can also mean loss.

Data indicating reservoir variables corresponding to these small values -> avoid infill drilling!

Data indicating reservoir variables corresponding to these high values -> do infill drilling!

... such data would lead to better decisions in this situation.

Value of information (VOI)

Prior value:

$$PV = \max_{\boldsymbol{a} \in A} \left\{ E\left(v(\boldsymbol{x}, \boldsymbol{a}) \right) \right\}$$

Posterior value:

$$PoV\left(\boldsymbol{y}\right) = \int \max_{\boldsymbol{a} \in A} \left\{ E\left(v\left(\boldsymbol{x}, \boldsymbol{a}\right) \mid \boldsymbol{y} \right) \right\} p\left(\boldsymbol{y}\right) d\boldsymbol{y}$$

VOI = Expected posterior value – Prior value

$$VOI\left(\boldsymbol{y}\right) = PoV\left(\boldsymbol{y}\right) - PV$$

$\boldsymbol{x}$ - Uncertainties

$\boldsymbol{a}$ - Alternatives

$v\left(\boldsymbol{x}, \boldsymbol{a}\right)$ - Value function

$\boldsymbol{y}$ - Data

Information gathering and VOI

VOI is interpretable as follows:

- **Is VOI larger than price of time-lapse seismic experiment?**

- Is VOI larger for seismic acquisition design A or B ?

- Is VOI larger for seismic processing type I or II ?

Computation - Formula for VOI

$$PV = \max_{a \in A} \left\{ E\left(v(\boldsymbol{x}, \boldsymbol{a}) \right) \right\} = \max_{a \in A} \left\{ \int_{\boldsymbol{x}} v(\boldsymbol{x}, \boldsymbol{a}) p\left(\boldsymbol{x} \right) d\boldsymbol{x} \right\}$$

$$PoV\left(\boldsymbol{y} \right) = \int \max_{a \in A} \left\{ E\left(v\left(\boldsymbol{x}, \boldsymbol{a} \right) \mid \boldsymbol{y} \right) \right\} p\left(\boldsymbol{y} \right) d\boldsymbol{y}$$

Main challenge.

Approximate computation

Outer expectation: $\boldsymbol{y}$

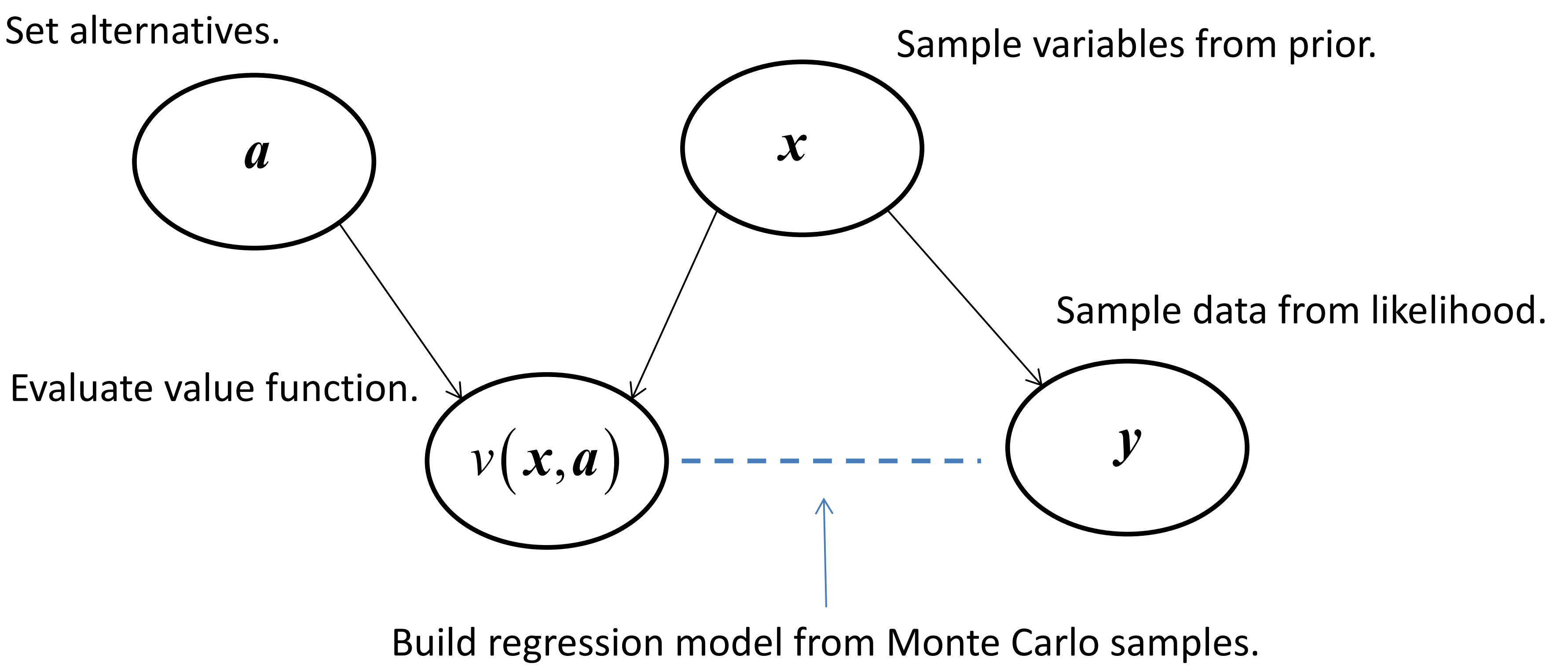
$$PoV\left(\boldsymbol{y}\right)=\int \max_{\boldsymbol{a}\in A}\left\{E\left(v\left(\boldsymbol{x},\boldsymbol{a}\right)\mid \boldsymbol{y}\right)\right\}p\left(\boldsymbol{y}\right)d\boldsymbol{y}$$

Inner expectation: $\boldsymbol{x}\mid \boldsymbol{y}$

$$VOI\left(\boldsymbol{y}\right)=PoV\left(\boldsymbol{y}\right)-PV$$

- **Suggest Monte Carlo (outer) and regression approximation (inner).**

Simulation-regression illustration



Simulation-regression algorithm

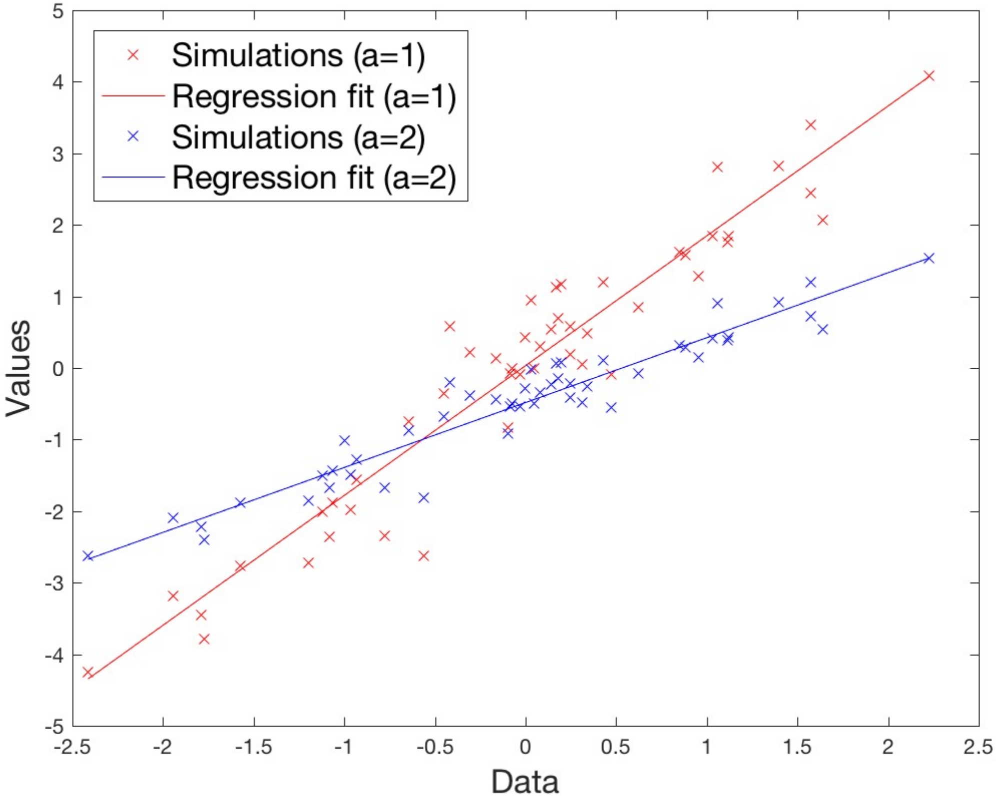
$$PoV(\boldsymbol{y}) = \overbrace{\int \max_{\boldsymbol{a}\in \boldsymbol{A}} \left\{ \underbrace{E\left(v(\boldsymbol{x},\boldsymbol{a}) \mid \boldsymbol{y}\right)}_{\text{Inner expectation}} \right\} p(\boldsymbol{y}) d\boldsymbol{y}}^{\text{Outer expectation}}$$

1. Simulate uncertainties: $\boldsymbol{x}^b \sim p(\boldsymbol{x}), \quad b = 1,\ldots,B$
2. Compute values, for all alternatives: $v_{\boldsymbol{a}}^b = v\left(\boldsymbol{x}^b, \boldsymbol{a}\right), \quad b = 1,\ldots,B, \quad \boldsymbol{a} \in \boldsymbol{A}$
3. Simulate data: $\boldsymbol{y}^b \sim p\left(\boldsymbol{y} \mid \boldsymbol{x}^b\right), \quad b = 1,\ldots,B$
4. Regress samples to fit conditional mean: $\hat{E}(v_a \mid \boldsymbol{y})$

$$PoV(\boldsymbol{y}) \approx \frac{1}{B}\sum_{b=1}^{B} \max_{\boldsymbol{a}\in \boldsymbol{A}} \left\{ \hat{E}\left(v_{\boldsymbol{a}} \mid \boldsymbol{y}^b\right) \right\}$$

Illustration - fit regression model to samples

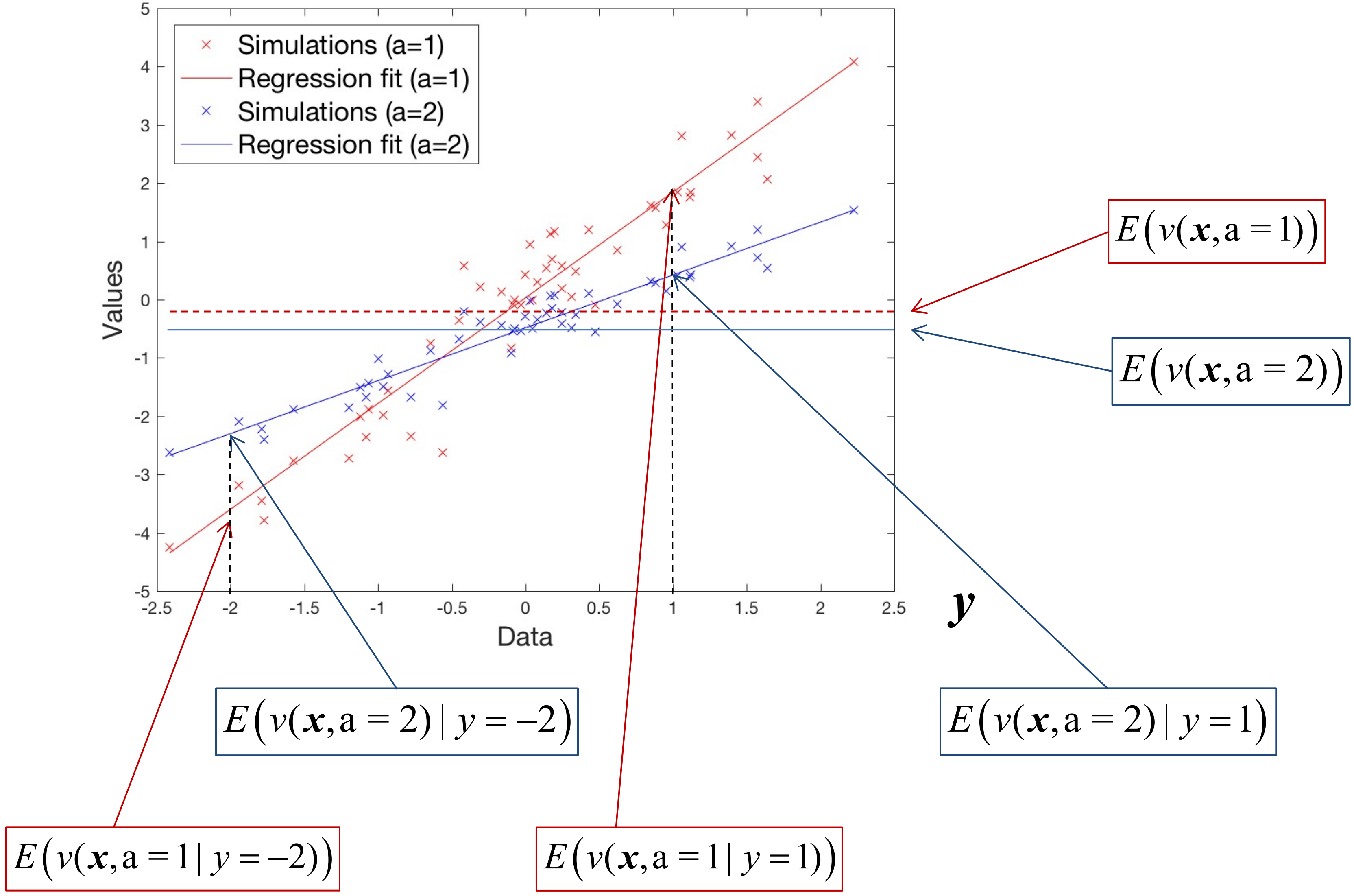
$v(\boldsymbol{x}, \boldsymbol{a})$



$\boldsymbol{y}$

Illustration - fit regression model to samples

$v(\boldsymbol{x}, \boldsymbol{a})$



Choice of regression method

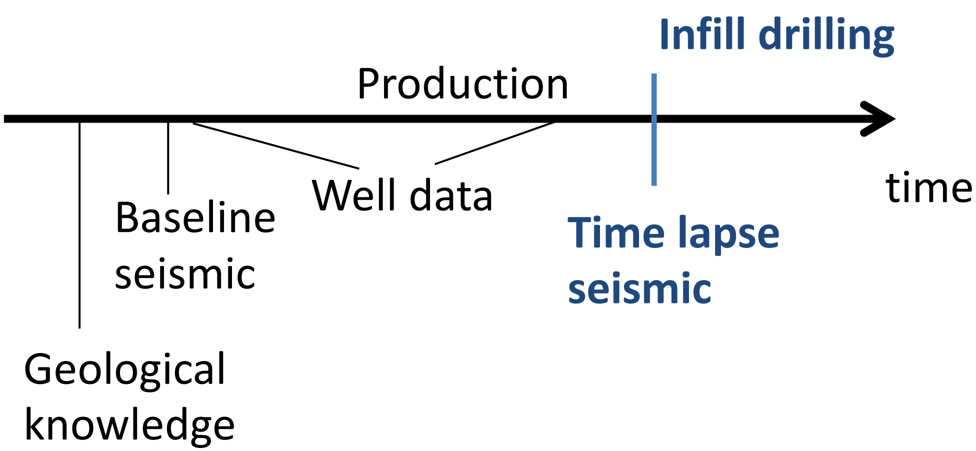
- Linear regression
- Principal component regression
- Partial Least squares
- Neural networks
- K-nearest neighbors
- Random forest
- and many others

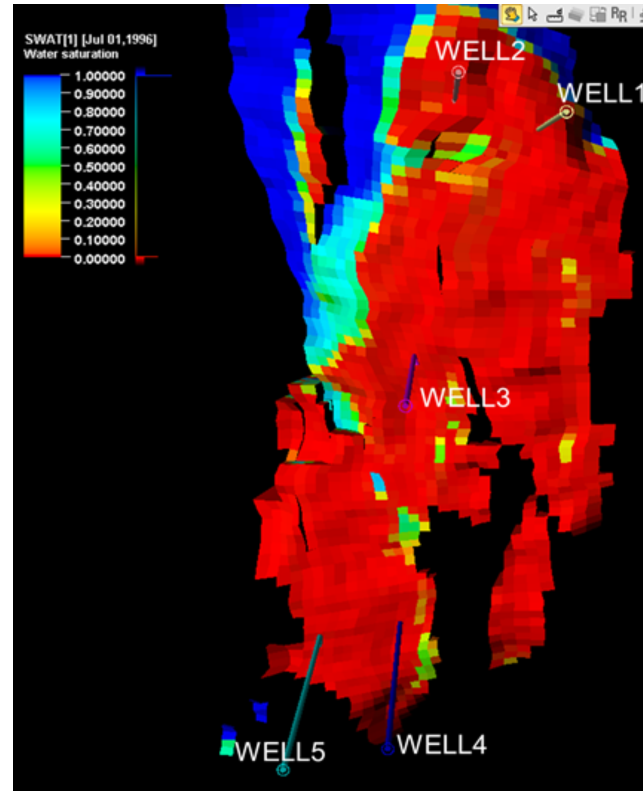
- Cross-validation to check model fit, look at residuals, etc.

Gullfaks case (infill drilling and time lapse)

Time-lapse seismic has shown useful at Gullfaks. But no formal VOI analysis was conducted up-front.

We consider this case in retrospect.





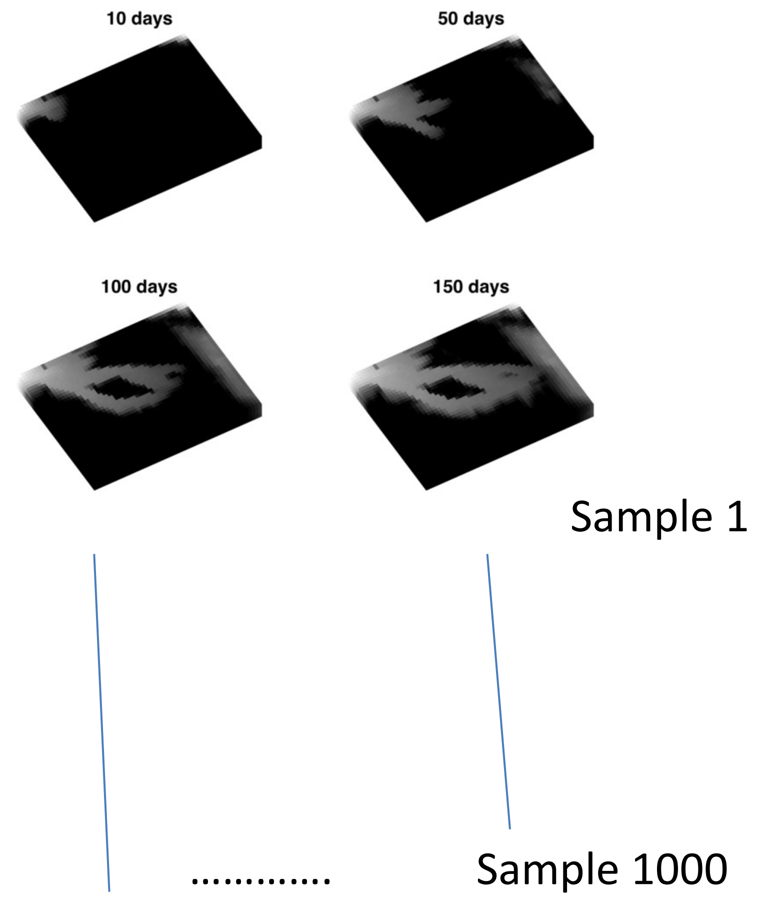
5 decision alternatives.

Prior - Reservoir uncertainty

Uncertainties: saturation, pressure, porosity, permeability and fault transmissibilities. (Conditioned on existing data.)

Prior is $p(\boldsymbol{x})$.

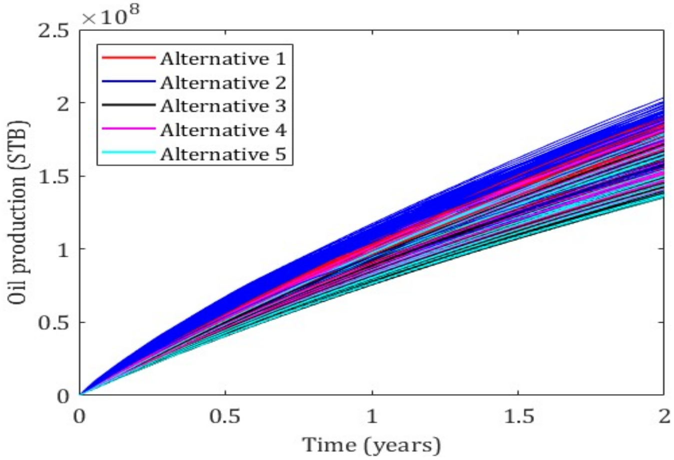
This distribution of reservoir variables is represented by multiple Monte Carlo realizations from the prior distribution.

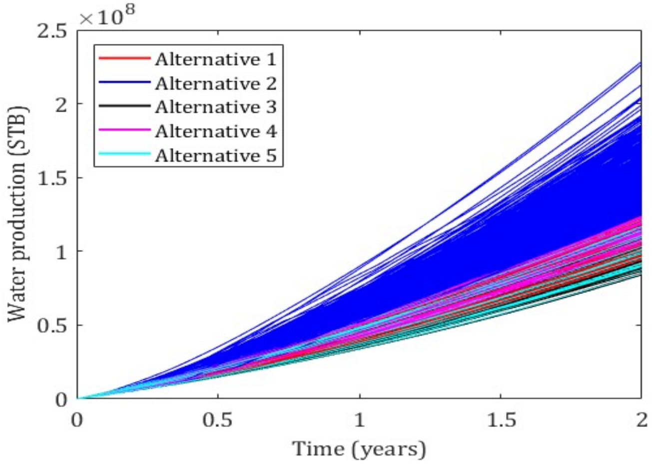


Gullfaks case (values)

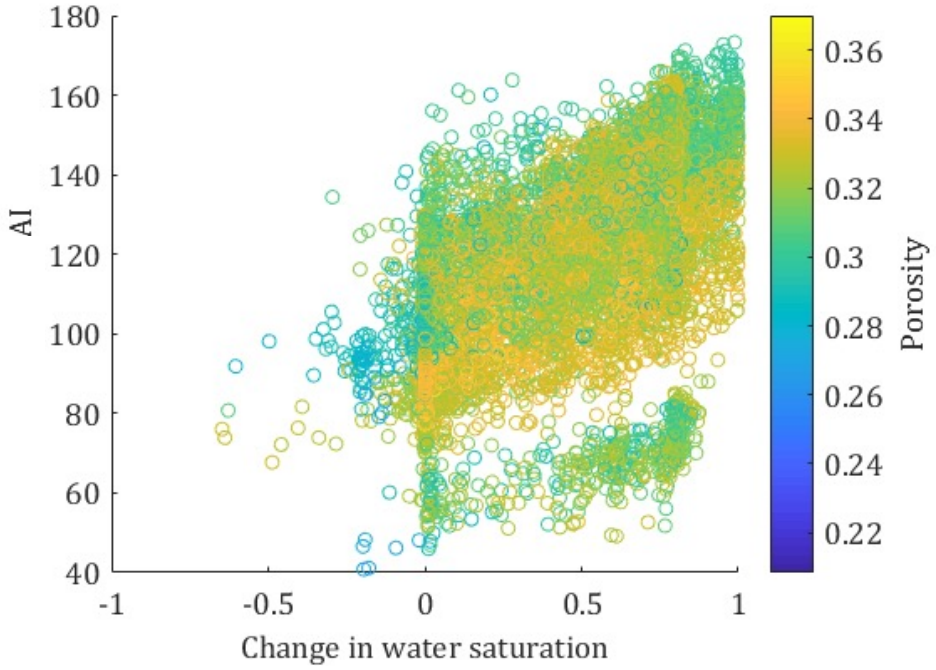
Future production for 5 different infill drilling alternatives.

- for each realization, all alternatives are «produced».





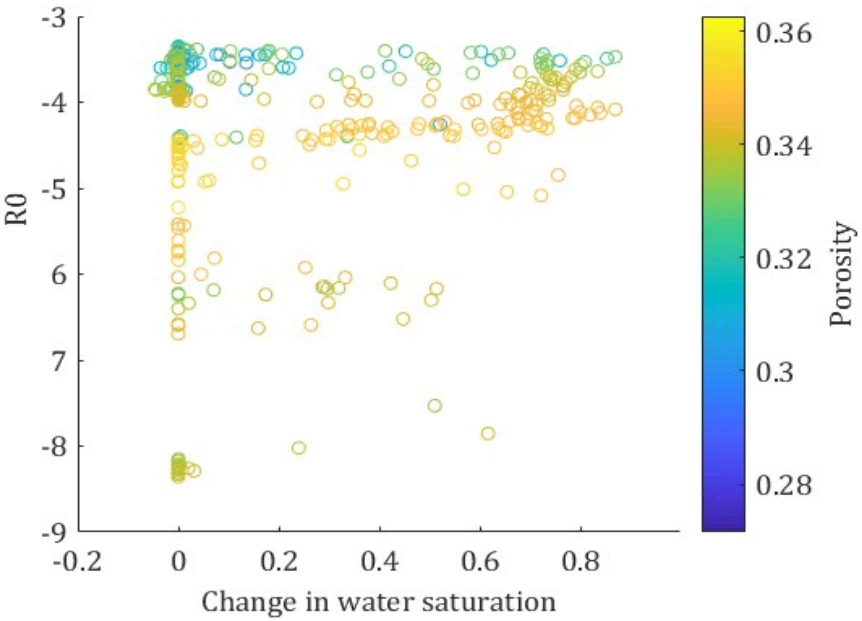
Gullfaks case (likelihood of AI data)

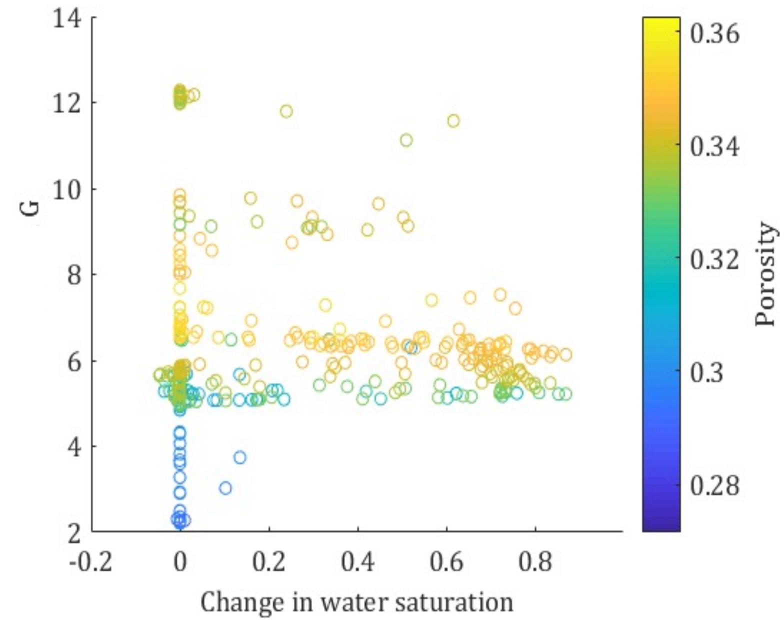


Synthetic time-lapse seismic (acoustic impedance (AI) proessing):
Use rock physics relations connecting reservoir properties to AI.

Simulations indicate some information about saturation from AI for this case.

Gullfaks case (likelihood of R0,G data)

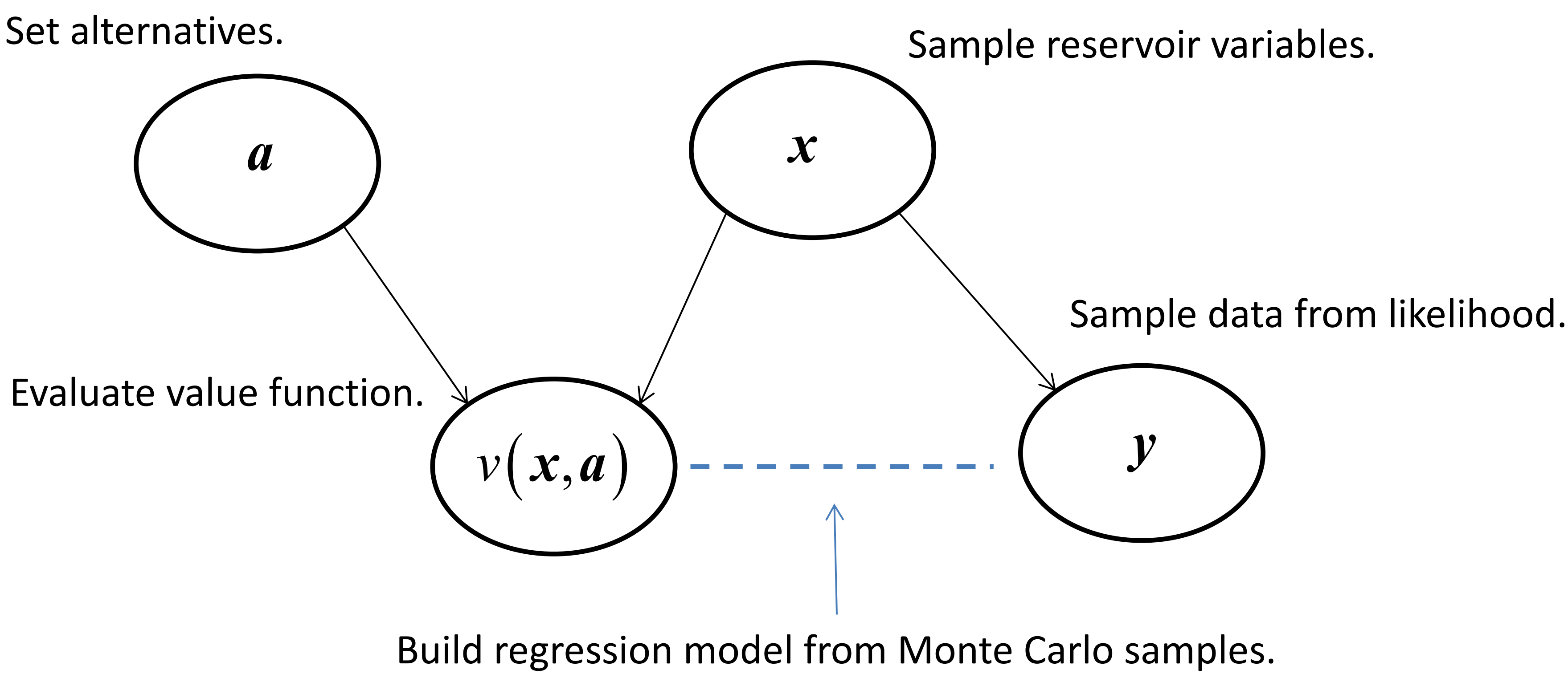




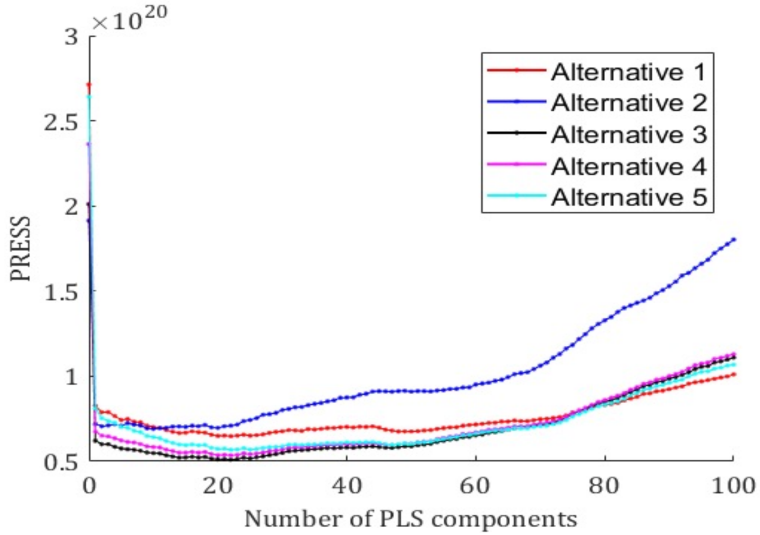
Synthetic time-lapse seismic (processing more angle information (R0,G)):
Use rock physics relations.

Simulations indicate limited information about saturation from (R0, G).

Simulation-regression illustration



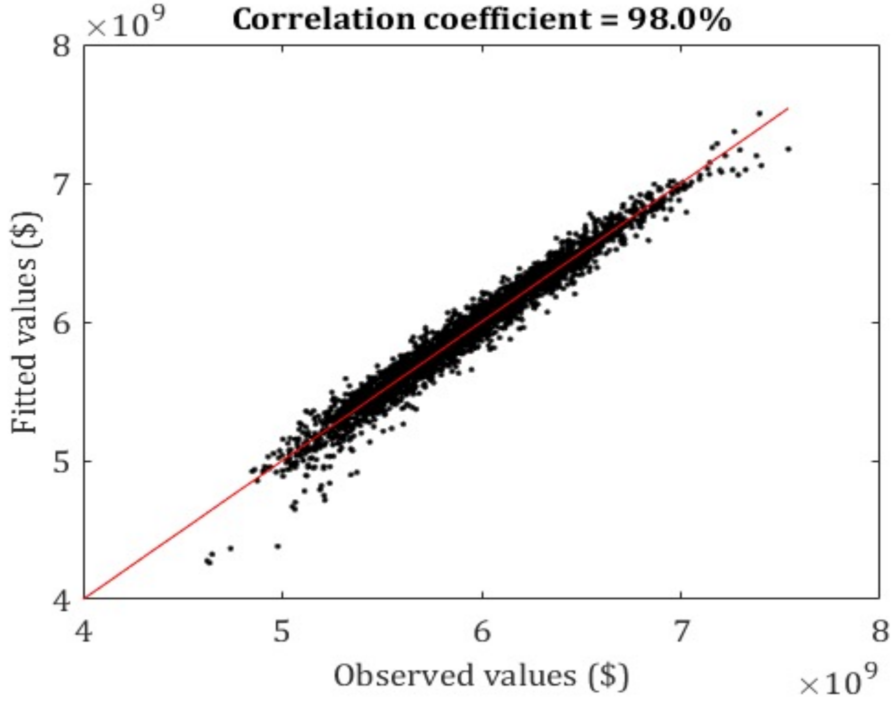
Gullfaks case (PLS for expected values)



- Partial least squares (PLS) is used for regressing values on large seismic data set.
- Cross-validation to find optimal number of linear combinations.
- PLS is similar to Principle component regression (PCR).

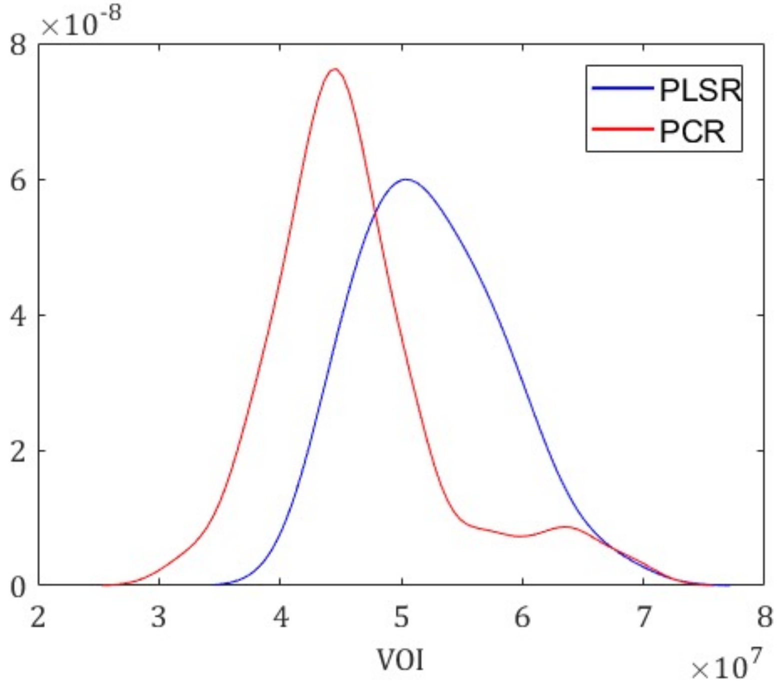
(PLS focuses on explaining covariance instead of variance.)

Gullfaks case (predictive power)

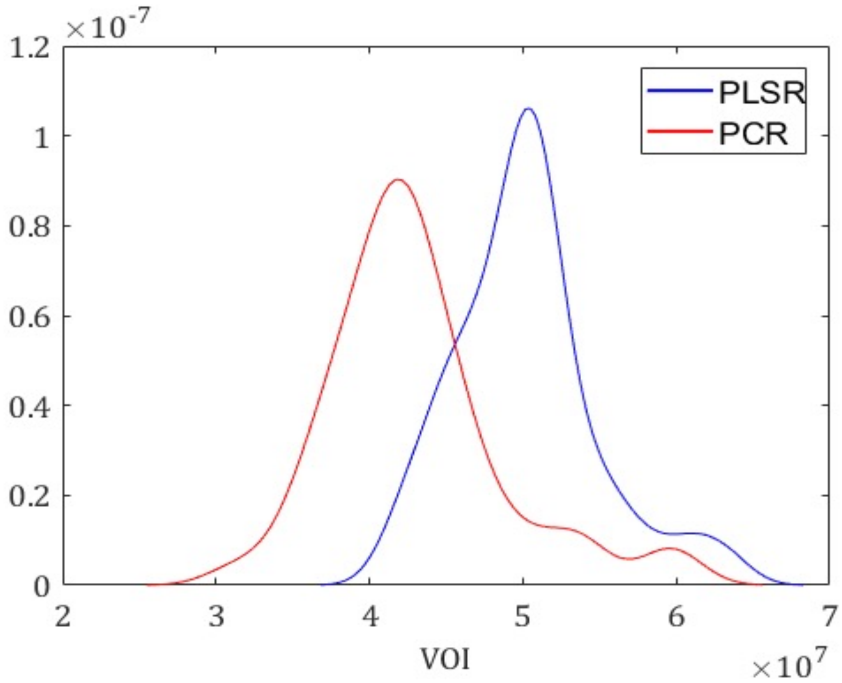


Fit of PLS regression is reasonable (based on AI data here).

Gullfaks case (VOI results)



Acoustic impedance (AI)

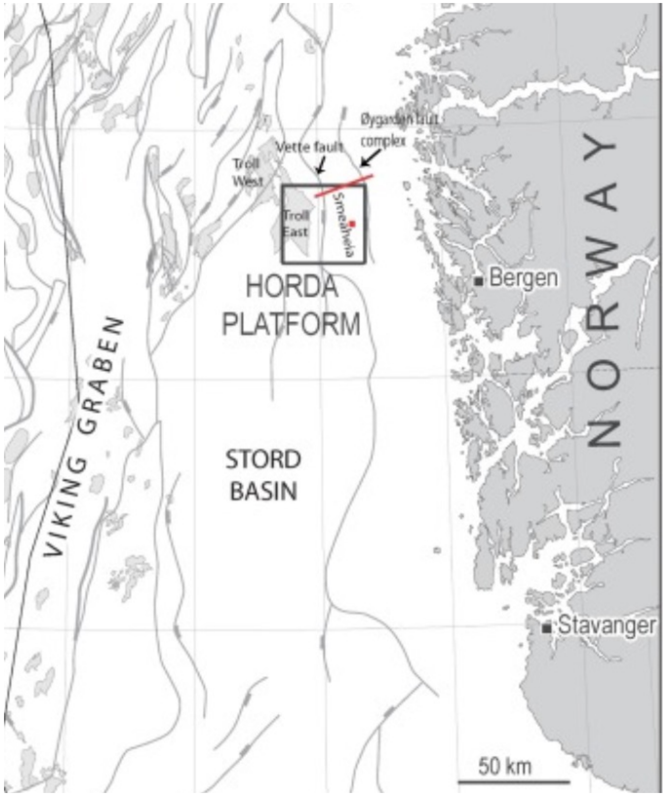


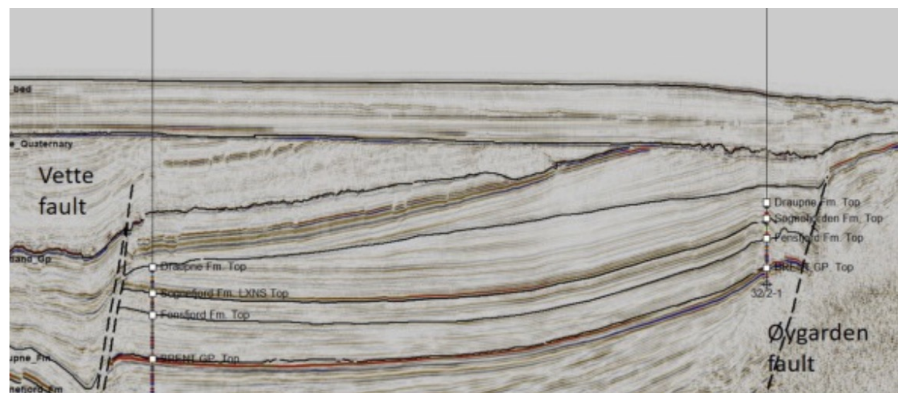
Angle information, (R0,G)

VOI of time-lapse data is about $50 million.
No big differences in VOI of processing methods
(but the price of these likely differ).

(Bootstrap used to get distribution.)

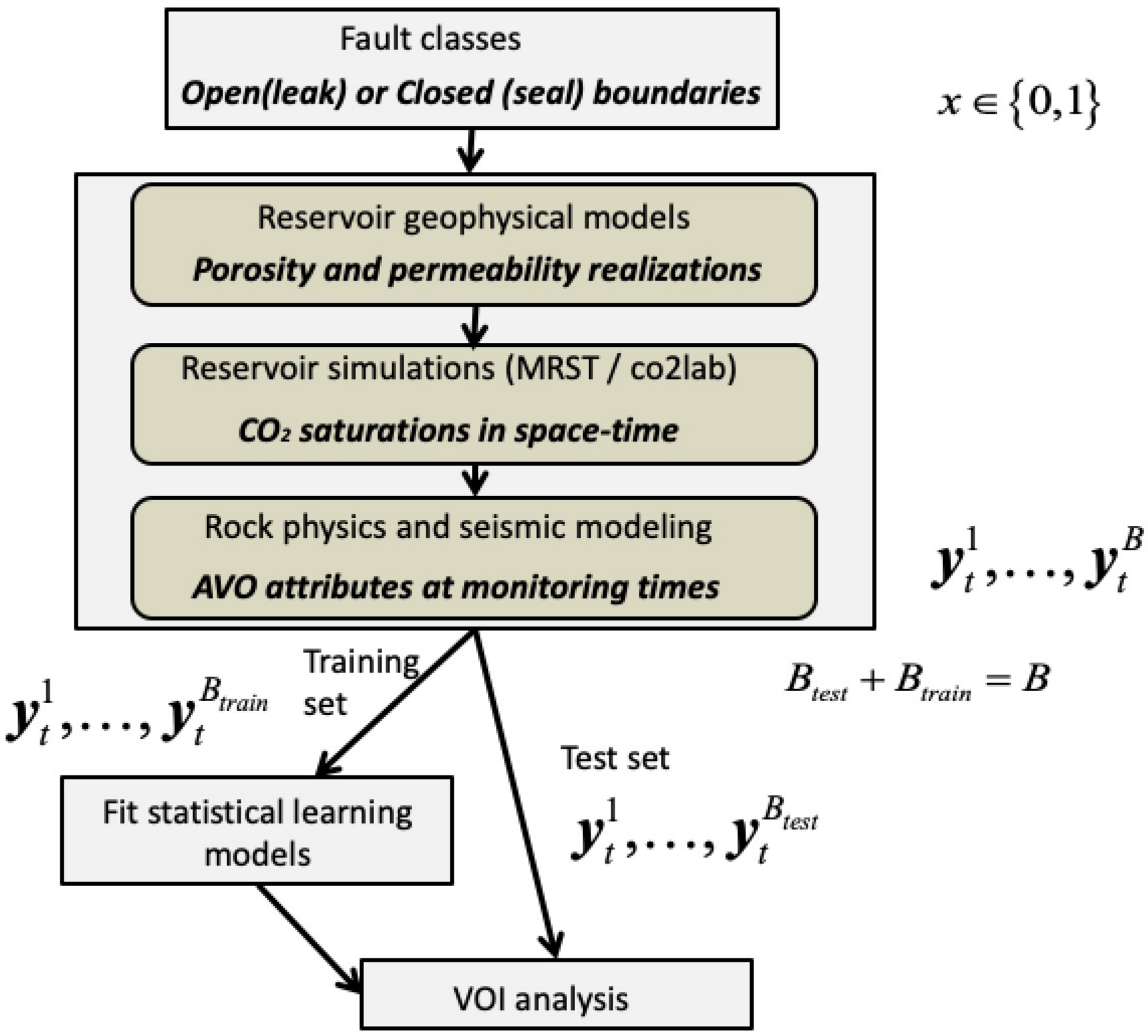
Smeaheia case



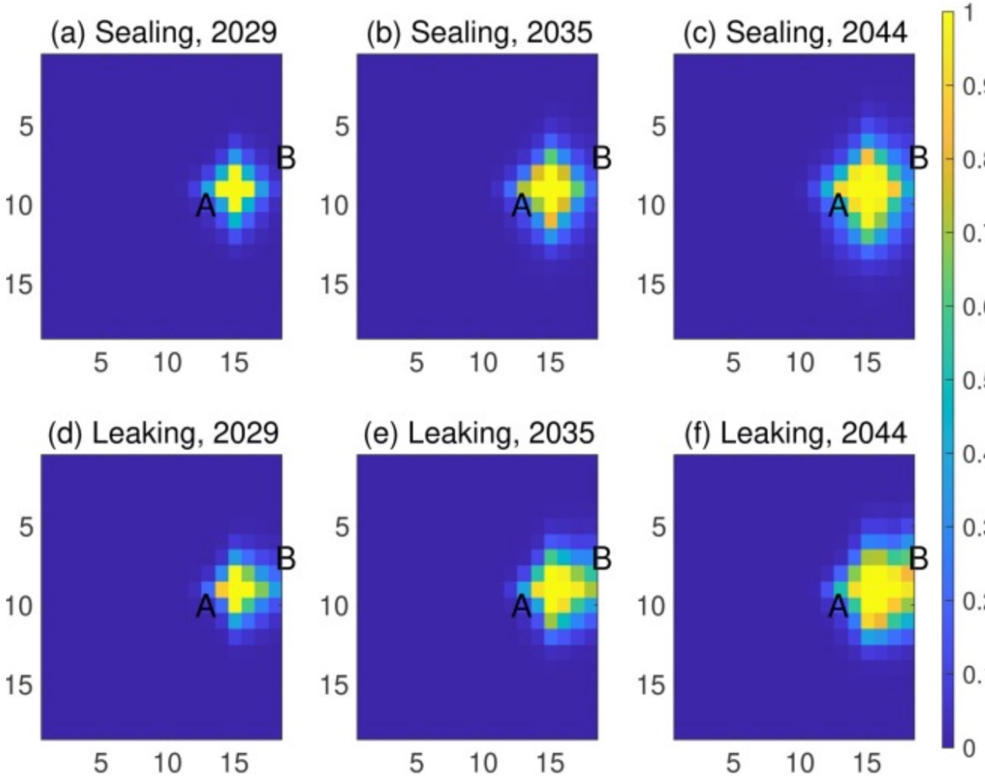


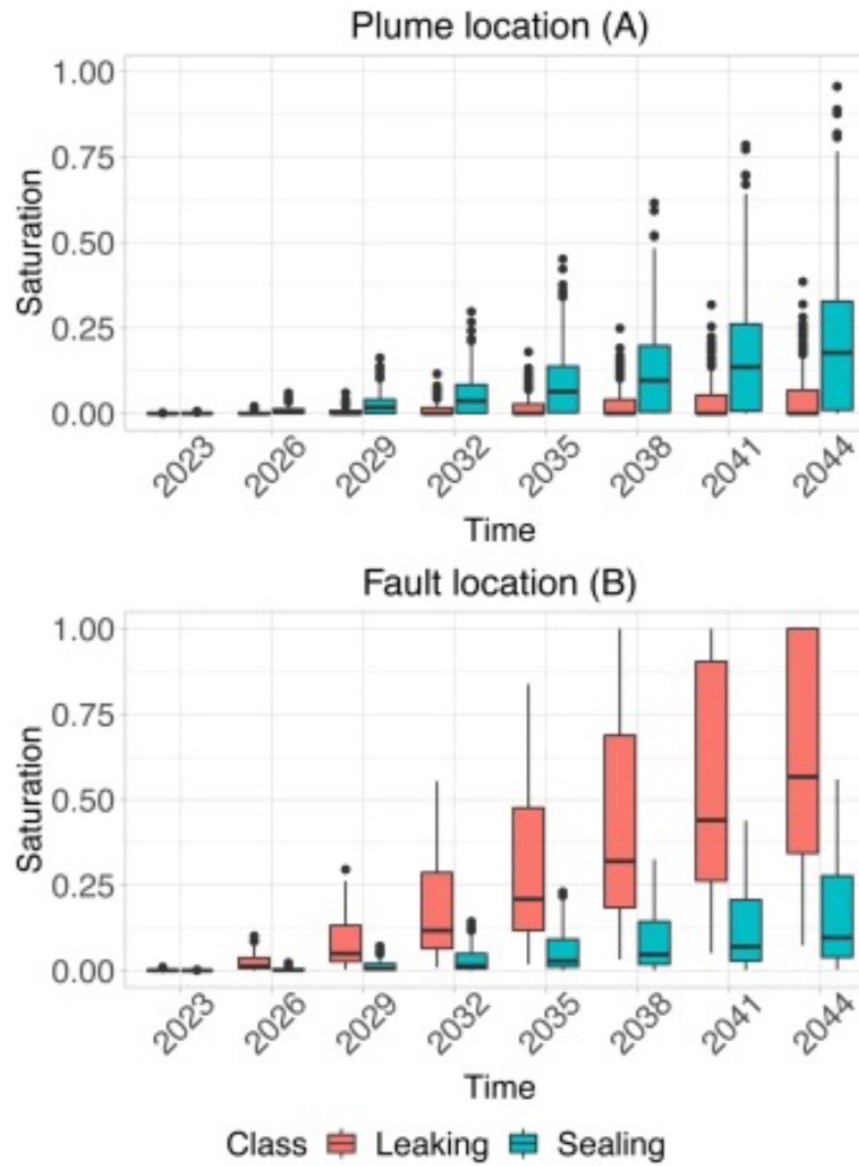
Injected CO2 can leak. When is the best time to conduct seismic time lapse monitoring.

Geostatistics and reservoir simulations



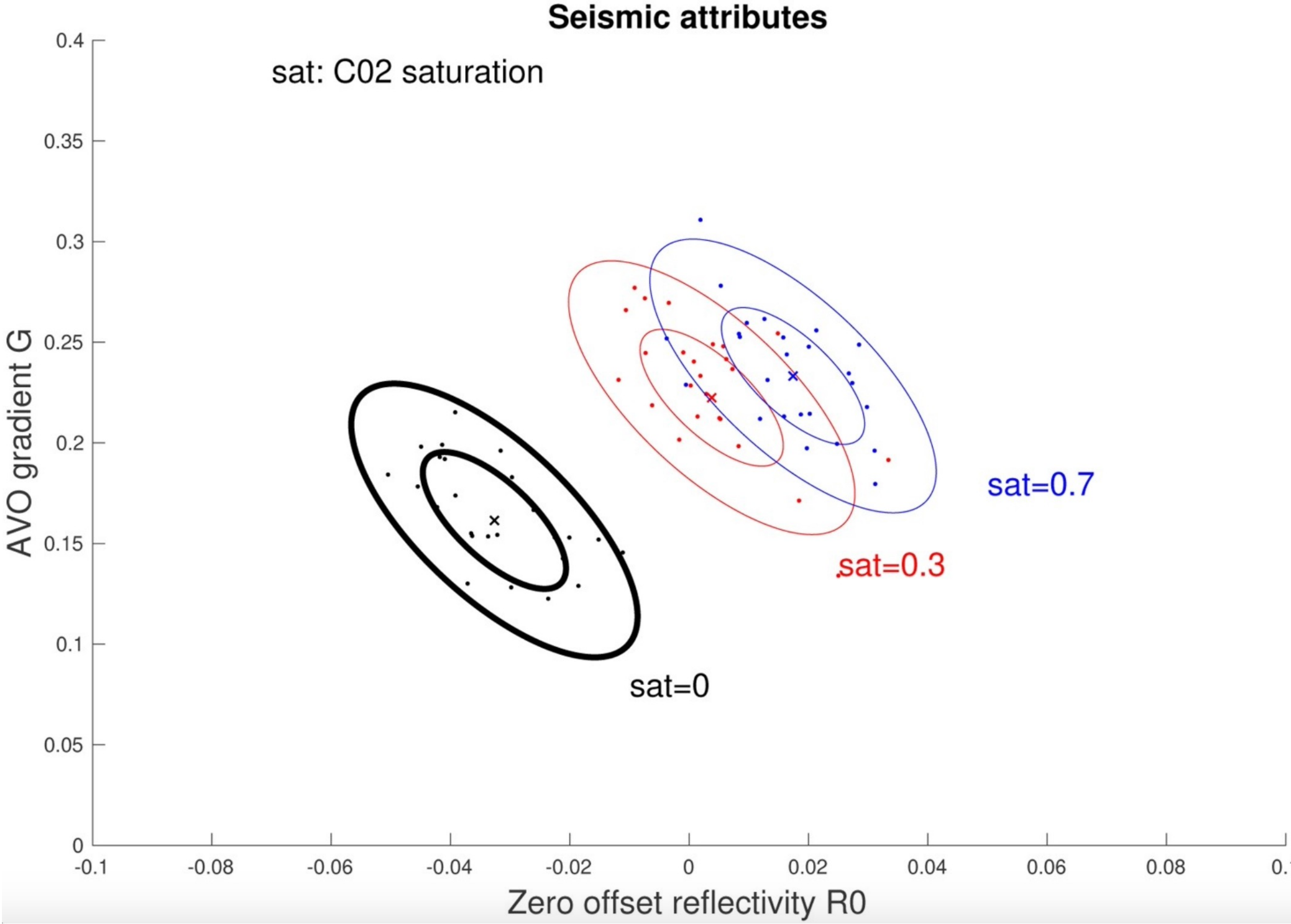
Simulations under leak / seal





Using MRST /CO2lab,
10000 realizations.

Seismic data



Fitted Gaussian likelihoods. Not always easy to discriminate a little or high CO2 saturation.

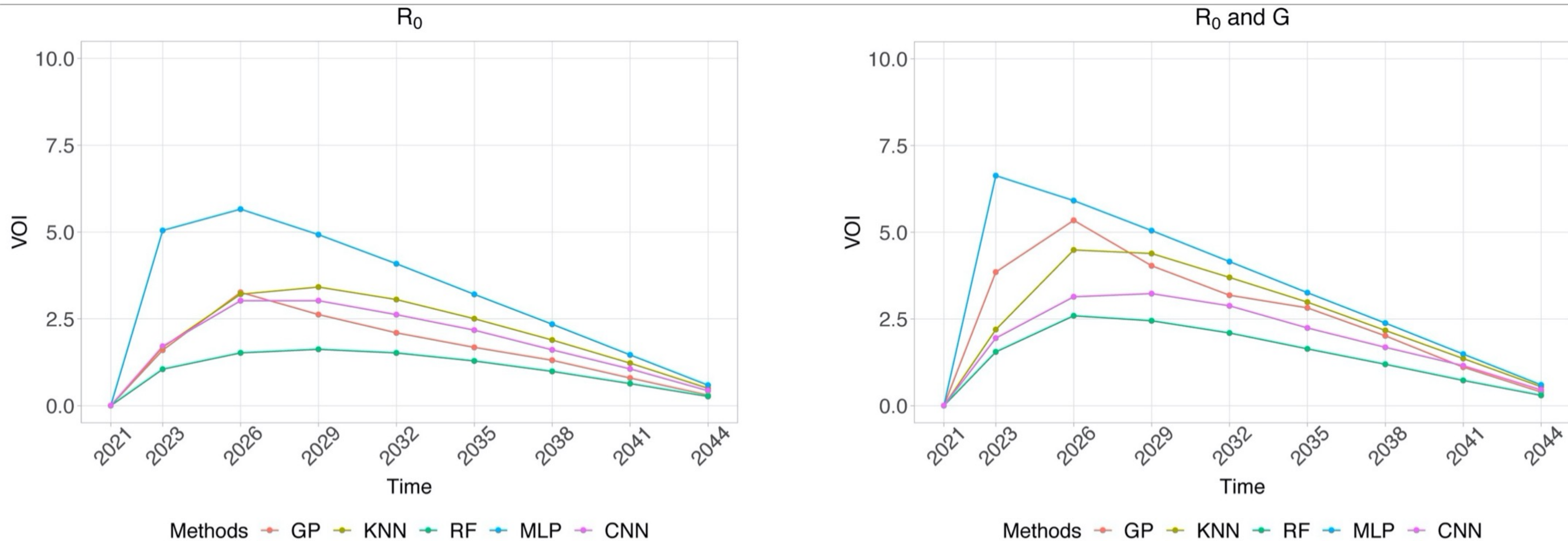
Value function

$$\begin{aligned}\mathrm{VOI}_t \;&\approx\; \frac{1}{B_{\mathrm{test}}}\sum_{b=1}^{B_{\mathrm{test}}} \max\nolimits_{a\in A}\left\{\sum_{x=0}^{1} v_t(x,a)\widehat{P}(X=x|\boldsymbol{y}_t^b)\right\} \\ &-\; \max\nolimits_{a\in A}\left\{\frac{1}{B_{\mathrm{test}}}\sum_{b=1}^{B_{\mathrm{test}}}\sum_{x=0}^{1} v_t(x,a)\widehat{P}(X=x|\boldsymbol{y}_t^b)\right\}.\end{aligned}$$

Value function is associated with stop or continue injecting alternatives, and leak or seal outcomes.

Different machine learning approaches are used to estimate the conditional leak / seal probabilities.

VOI results



R_0
R_0 and G
VOI
10.0
7.5
5.0
2.5
0.0
2021
2023
2026
2029
2032
2035
2038
2041
2044
Time
Methods GP KNN RF MLP CNN

Closing remarks

- VOI to determine what are useful data gathering plans.
  Here **time-lapse seismic data**
- Frame decision situation - alternatives and uncertainties.
  Here **infill drilling plans or stop / continue injection**.
- Computationally difficult – approach requires approximations.
  Simulation-regression : i) generate realizations of values and data,
  ii) fit conditional expectation of values.

Future : Continuous monitoring. (Johan Sverdrup field – digitalization)
When/where/how is it most valuable to process data.

Artificial Intelligence, Internet of Things, Active Learning :
All tied to smart decisions and efficient ways of gathering or processing data.