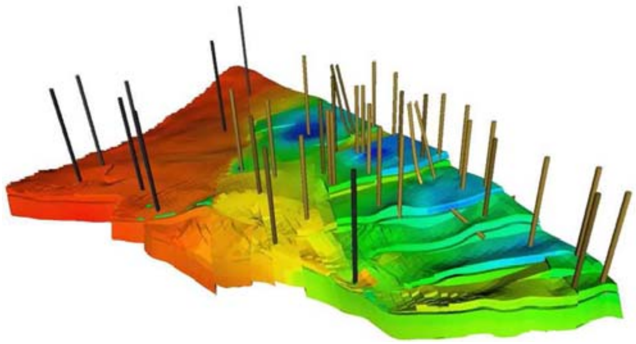

Model-Based Control and Optimization of Large Scale Physical Systems

Challenges in reservoir engineering

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co-authors: Jan Dirk Jansen, Gijs van Essen, Okko Bosgra

Chinese Control and Decision Conference, Guilin, China, 19 June 2009

Delft University of Technology

Oldest and largest of 3 Technical Universities in the Netherlands:
Delft – Eindhoven - Twente

Founded in 1842 as an engineering school

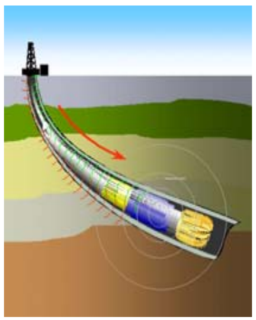
Now: 5000 employees, of which 2700 scientists, 15,000 students, distributed over 8 engineering faculties:

- Electrical, Math, Comp. Science
- Aerospace Engin.
- Applied Sciences
- Mechanical, Maritime, Mat. Eng.
- Civil Engin., Earth Sciences
- Industrial Design
- Techn. Policy Making and Manag
- Building Engineering

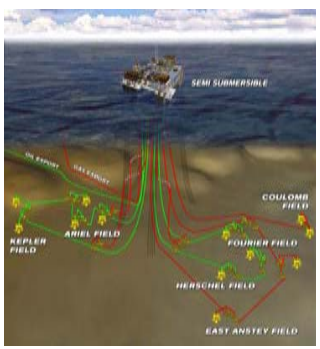
Upstream oil industry

production

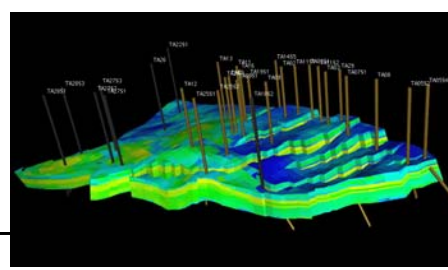
seismic imaging

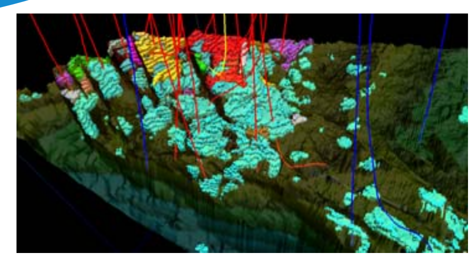


drilling



reservoir modeling





geological modeling

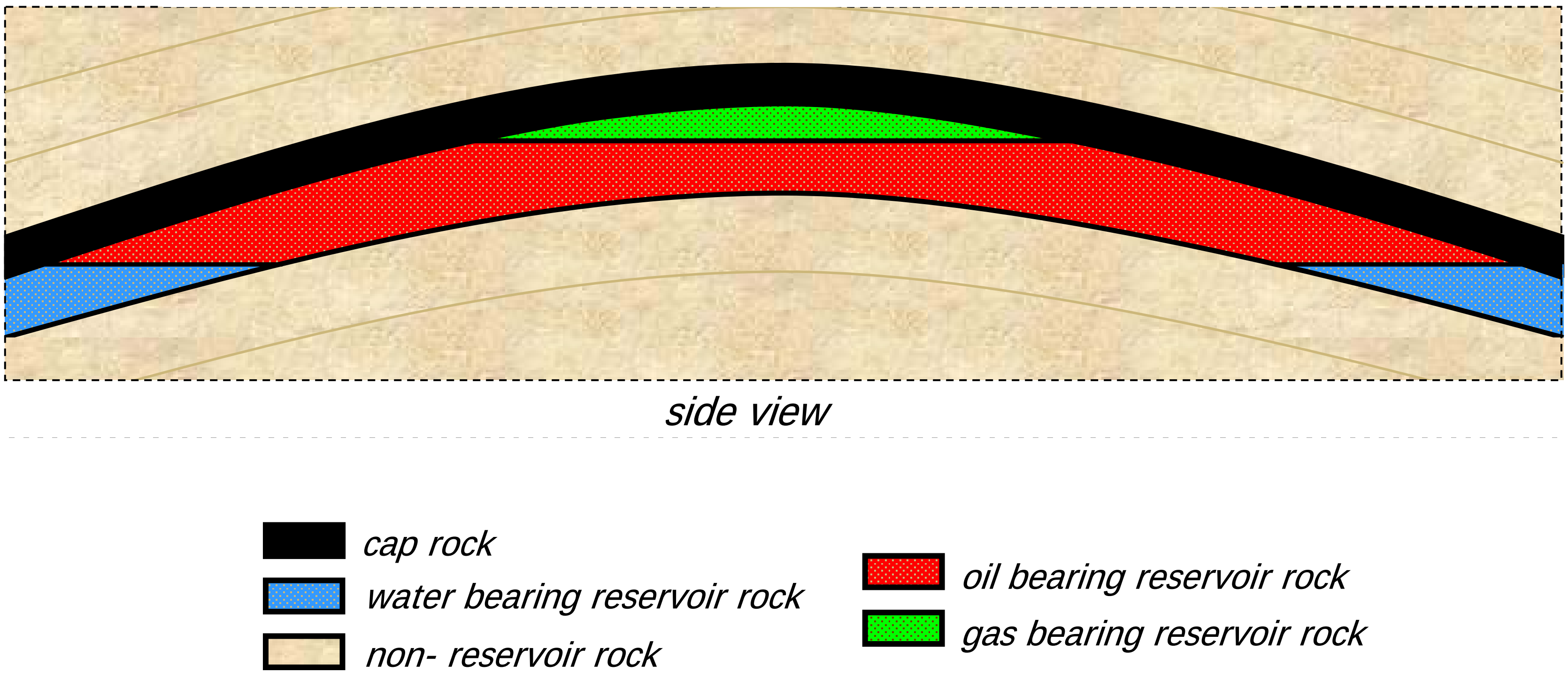
Contents

Upstream oil industry characteristics

- Capital intensive: well: 1-100·10^6 US$, field: 0.1-10·$10^9$ US$
- Uncertainty: geology, oil price, limited data
- Stretched in time scales:
  - production operations: day – weeks
  - field development – years
  - reservoir management: 10s of years
- Slow in response
- Many disciplines involved: geology, geophysics, reservoir engineering, production, drilling
- Remote
- New technology: horizontal drilling, multi-laterals, time lapse seismics, smart fields ….

Oil & gas reservoirs

fluids trapped in porous rock below an impermeable ‘cap rock’



Oil production mechanisms

- Primary recovery – natural flow

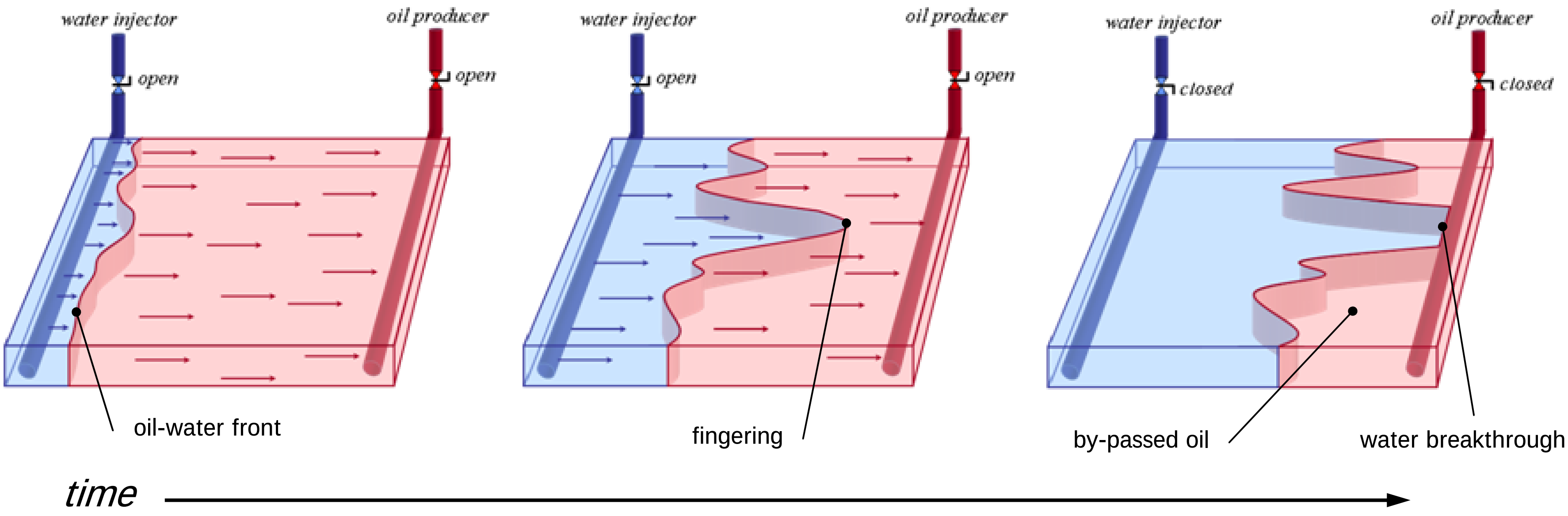
  (depletion drive, 5-15% recovery)
- Secondary recovery – injection of water or gas to maintain reservoir pressure and displace oil actively

  (water flooding, gas flooding, 20-70% recovery)
- Tertiary recovery – injection of steam or chemicals (polymers, surfactants) to change the in-situ physical properties (e.g. viscosity, surface tension)

  (steam flooding, polymer flooding, 20-90% recovery)

Waterflooding

- Involves the injection of water through the use of injection wells
- Goal is to increase reservoir pressure and displace oil by water
- Production is terminated when ratio between produced oil and water is no longer economically viable



R&D drivers

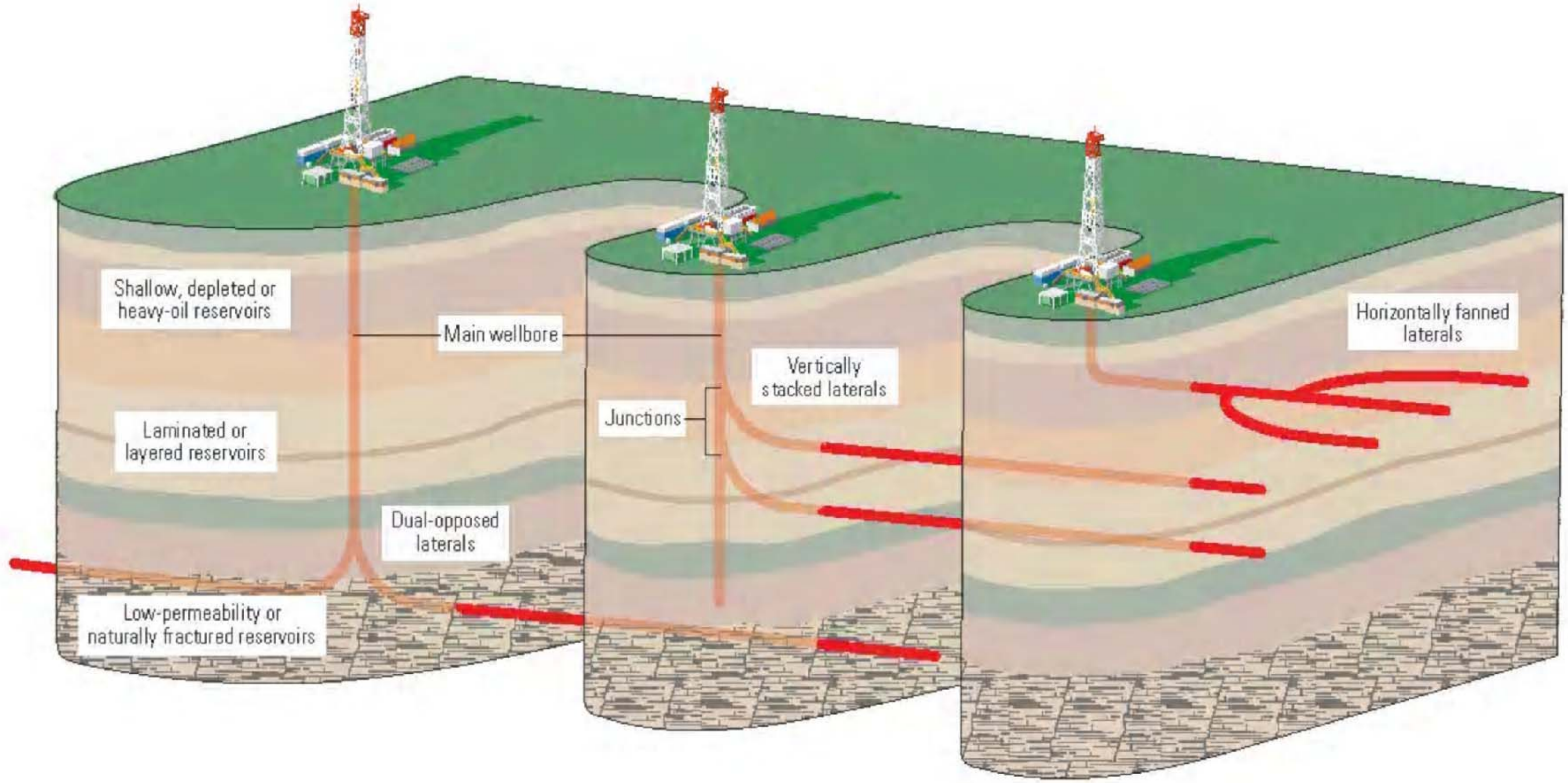
- Lower margins, higher complexity of developments
  - 'easy oil' has been found
  - pressure on cycle times

=> produce more from existing reservoirs

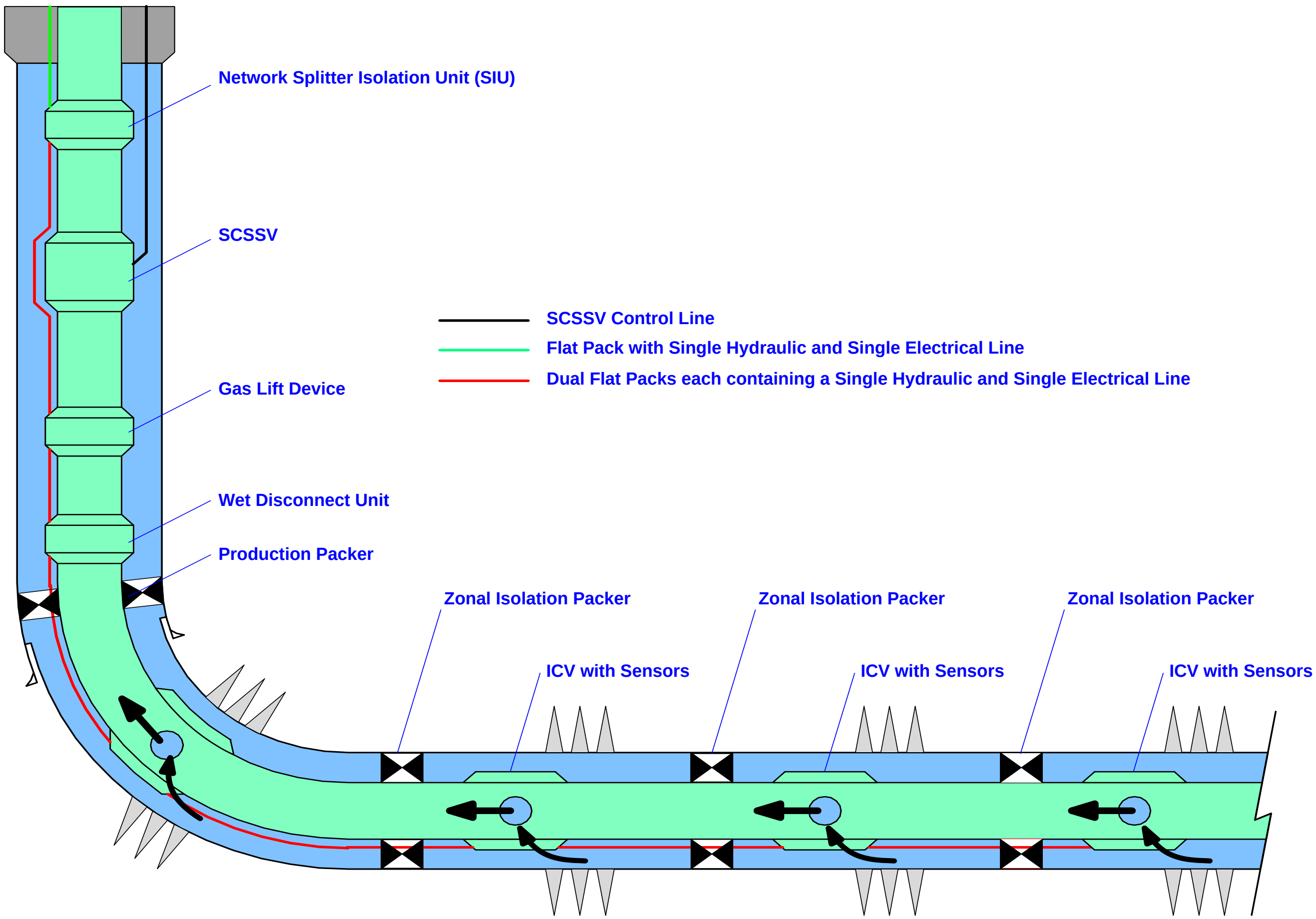
- Increasing knowledge- and data intensity
  - more sensors: pressure/temperature/flow, time-lapse seismics, passive seismics, EM, tilt meters, remote sensing, ...
  - more control: multi-lateral wells, smart wells, snake wells, dragon wells, remotely controlled chokes, ...
  - more modelling capacity: computing power, visualisation

=> use a model-based systems and control approach

Smart well with inflow control valves



Smart well with inflow control valves



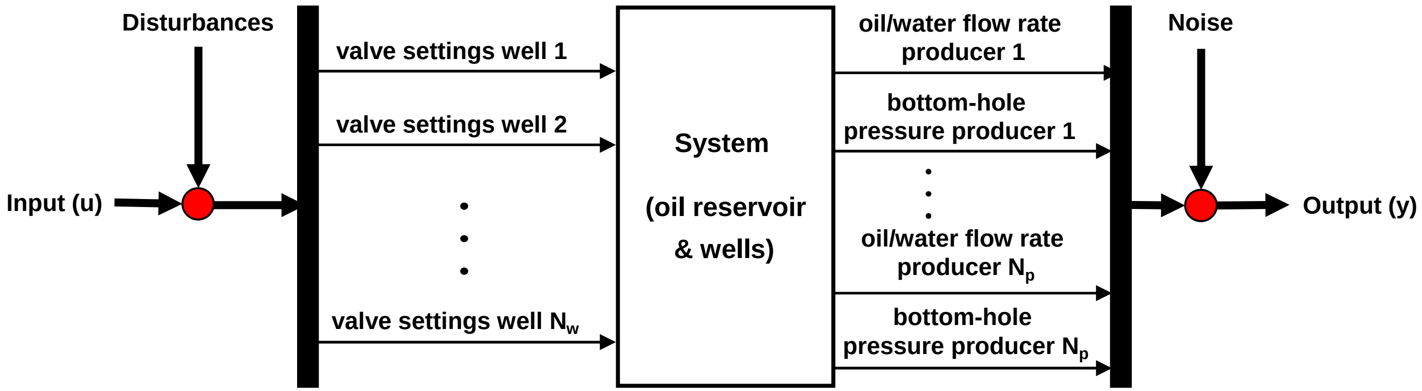
Main question to explore:

Can model-based control be of use in this field, to support the decision-making and operational strategies of the operators / field-managers ?

The Models

System involves the reservoir, wells and sometimes surface facilities

- Inputs: control valve settings of the wells (injectors and producers)
  - Smart wells: multiple (subsurface) valves
- Outputs: (fractional) flow rates and/or bottomhole pressures
  - Smart wells: multiple (subsurface) measurement devices



Governing differential equations
isothermal two-phase (oil-water) flow

Mass balance:

$$\nabla(\rho_i u_i) + \frac{\partial}{\partial t}(\phi \rho_i S_i) = 0 \qquad i = \{o, w\}$$

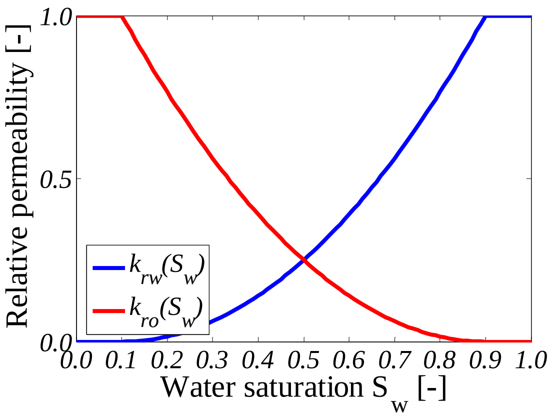
Momentum (Darcy's law):

$$u_i = -k \frac{k_{ri}}{\mu_i} \nabla p_i \qquad i = \{o, w\}$$

Variables: p_o, p_w, S_o, S_w

Saturations satisfy: $S_o + S_w = 1$

Simplifying assumptions, a.o.: $p_o = p_w$



Discretization in space and time

State space model:

$$
\begin{aligned}
V(x_t)\dot{x}_t &= T(x_t)x_t + q_t; \qquad x_0 \\
y_t &= h(x_t)
\end{aligned}
$$

$$
\begin{aligned}
y^T &= [p_{well}^T \; q_{well,o}^T \; q_{well,w}^T] \\
x^T &= [p_o^T \; S_w^T]
\end{aligned}
$$

After discretization in space (and time):

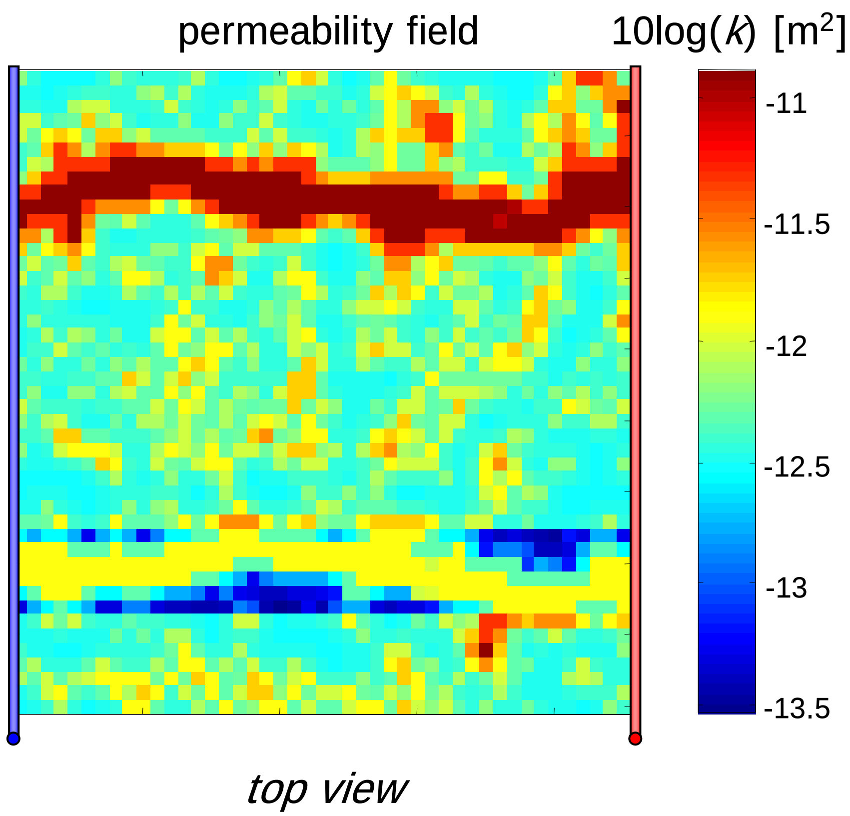
$$
g(x_{k+1}, x_k, u_k, \theta) = 0 \qquad dim(x) \approx 10^4 - 10^6
$$

$$
y_k = h(x_k)
$$

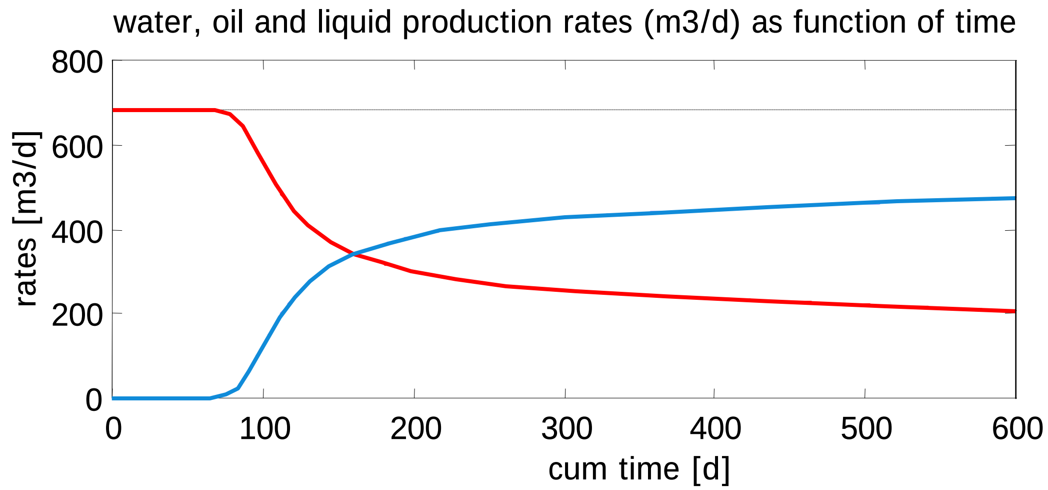
and θ typically the permeabilities in each grid block

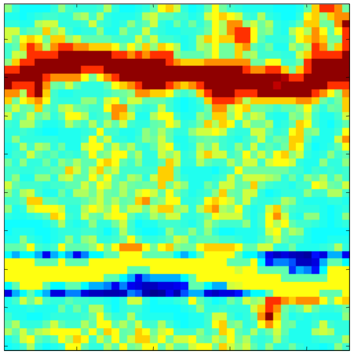
Reservoir simulation: Toy problem

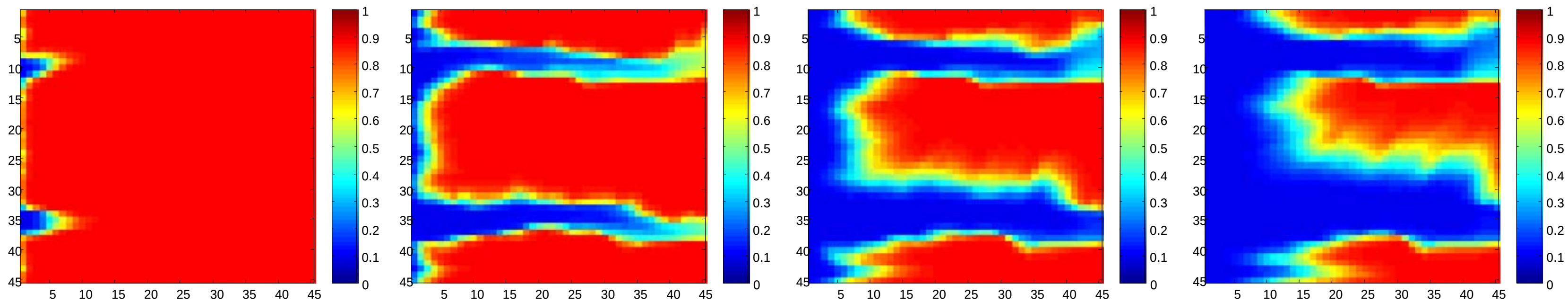
- 45 x 45 grid blocks
- 2 horizontal wells
  - 1 injector, 1 producer
- Heterogeneous permeability
  - High-perm channels
- Balanced injection/production
  - $q_{inj} = q_{prod}$



Toy problem: conventional production

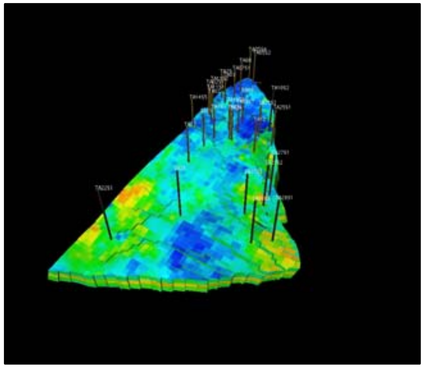






Equal pressures in all segments, at injection and production well

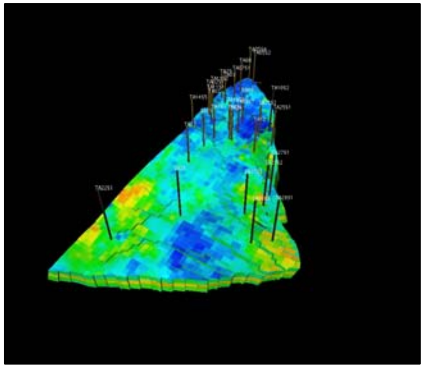
Reservoir flow models



- 3-phase (gas, oil, water) or multi-component
- Parameters: porosity, permeability, fluid properties
- Large variation in parameter values: $10^{-15} < k < 10^{-11}$ m^2
- Typical model size: 10^4 – 10^6 blocks, 50 – 500 time steps
- Spatial scale: 10^1-10^4 m
  - Grid block scale: 10^0-10^2 m
  - Inter-well distance 10^2-10^3 m
- MIMO: 10^0-10^3 wells

reservoir models are typically used in scenario-studies

Reservoir flow models



reservoir models are typically used in scenario-studies

- Extensively used in design phase: field (re-)development
- Hardly used in production phase (operations)

- Improvements of subsurface, spatially distributed actuation in (smart) wells create opportunities for model-based control in production phase
- Non-linear behavior of system and very long time horizon determine choice for physics-based reservoir flow models

Contents

- Introduction – the problem setting
- The models
- Model-based optimization
- Closed-loop reservoir management
- Parameter estimation and identifiability
- Additional optimization opportunities
- Prospects and conclusions

Model-based Optimization

Net present value (NPV):

- Goal: optimize economic cost function related to oil recovery, as a function of dynamic valve settings

$$J = \sum_{k=1}^{N} \frac{\Delta(t_k)[r_o q_{o,k} - r_w q_{w,k} - r_i q_{i,k}]}{(1+b)^{\frac{t_k}{\tau}}}$$

Under constraints: $c(x_k, u_k) \leq 0$

typically limits on water injection capacity, and max/min pressures in injection/production wells

Model-based Optimization

Optimization problem:

$$\max_q J(q) = \max_q \sum_{k=1}^{N} L(x_k, q_k)$$

such that: $g(x_{k+1}, x_k, q_{i,k}) = 0, \quad x_0 = x(0)$

$$q_{min} \leq q_k \leq q_{max}$$

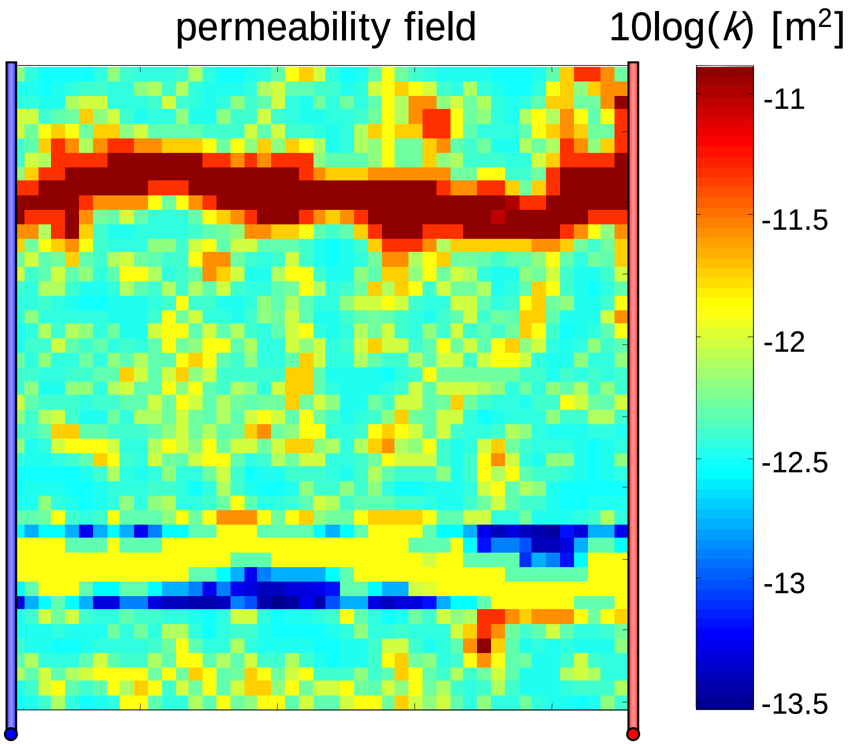
$$q_{o,k} + q_{w,k} = q_{i,k}$$

Non-convex optimization, solved by gradient-based method: Adjoint-variables calculation through backward integration of the related (Hamiltonian based adjoint) equation.
(feasible for systems of this size)

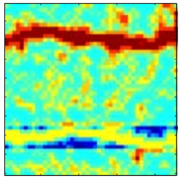
Model-based Optimization: Toy problem

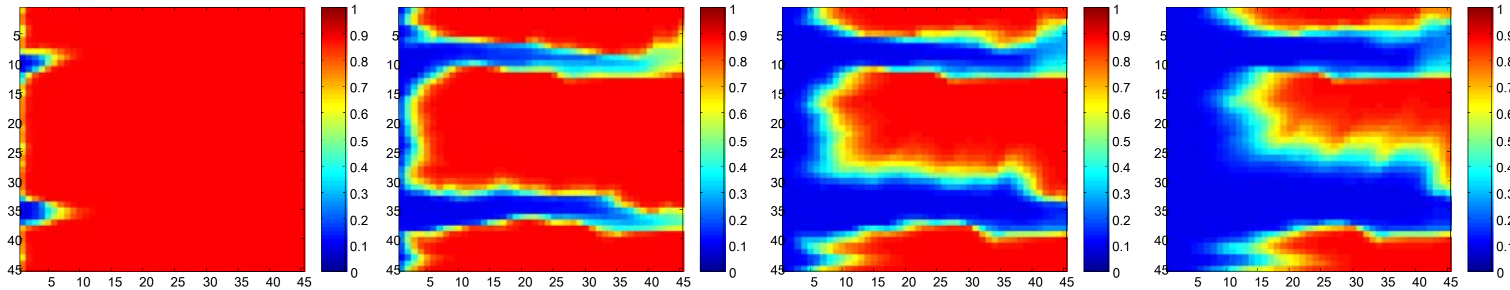
(Roald Brouwer et al, 2004)

- 2 horizontal smart wells
  - 45 inj. & prod. segments
  - Individually operated using subsurface control valve
- Balanced injection/production
  - $q_{inj} = q_{prod}$
- Objective function: NPV
  - oil price: r_o = 80 \$/m^3
  - water costs: r_w = 20 \$/m^3
  - discount rate: b = 0%

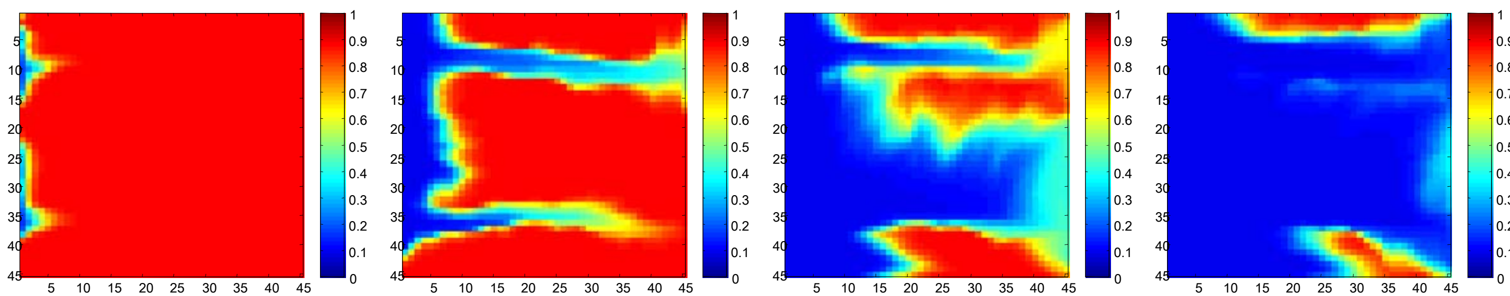


Toy problem, open-loop results (1)



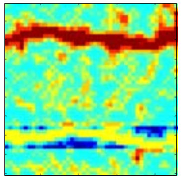


Conventional (equal pressure in all segments, no control)



Best possible (identical field rate, no pressure constraints)

Toy problem, open-loop results (2)



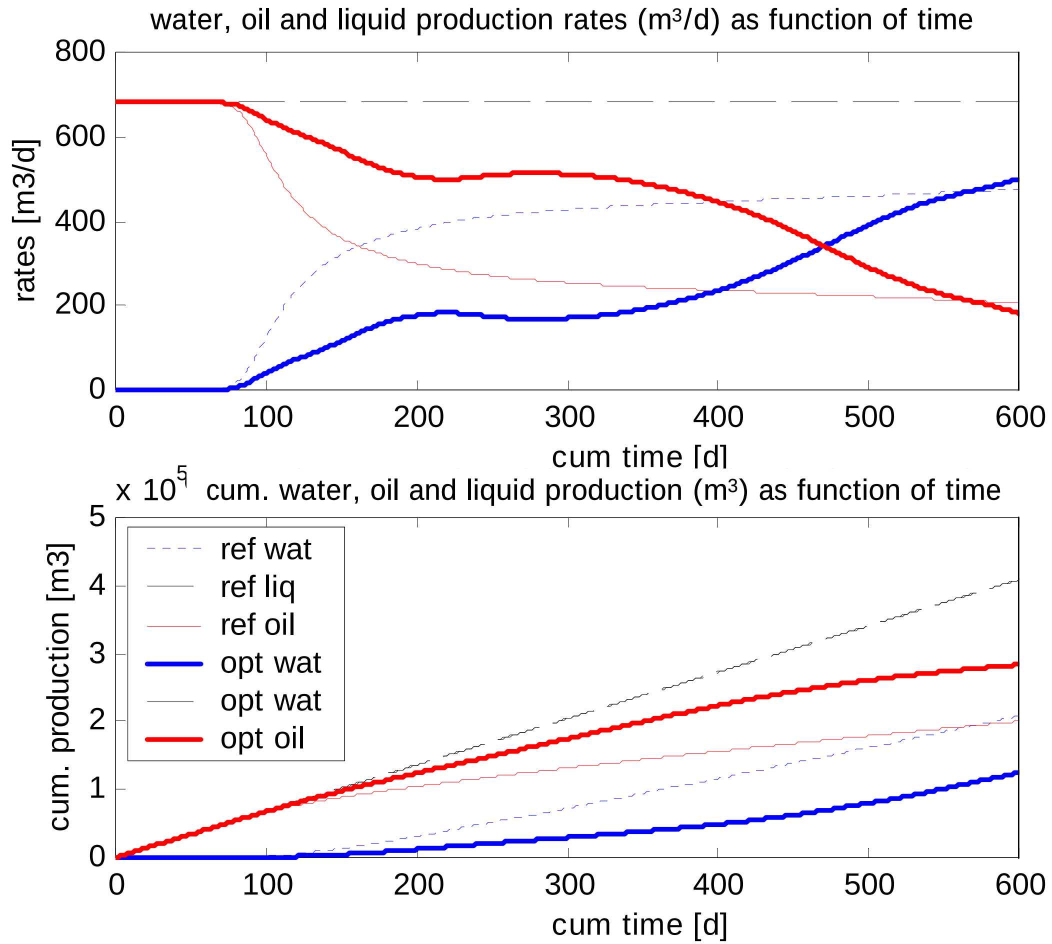
NPV

+ 60%

Production

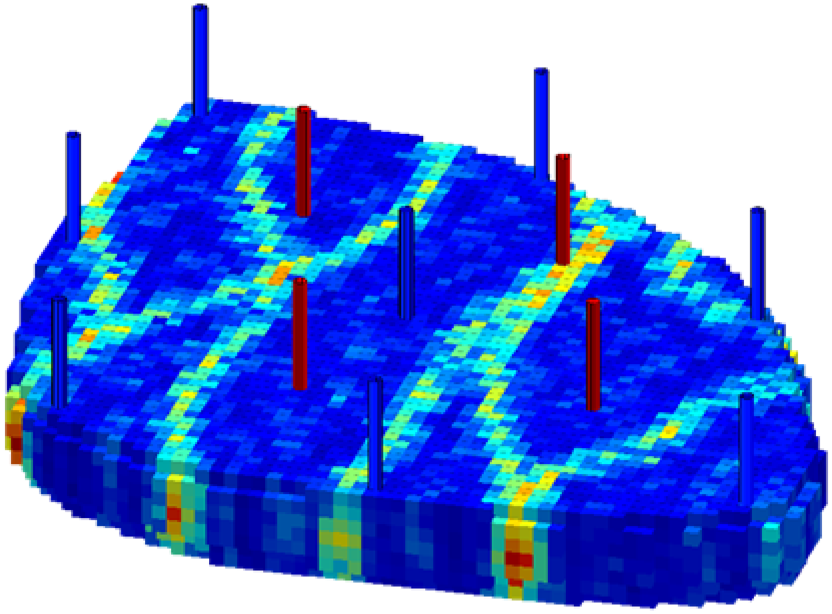
+ 41% cum oil

- 45% cum water

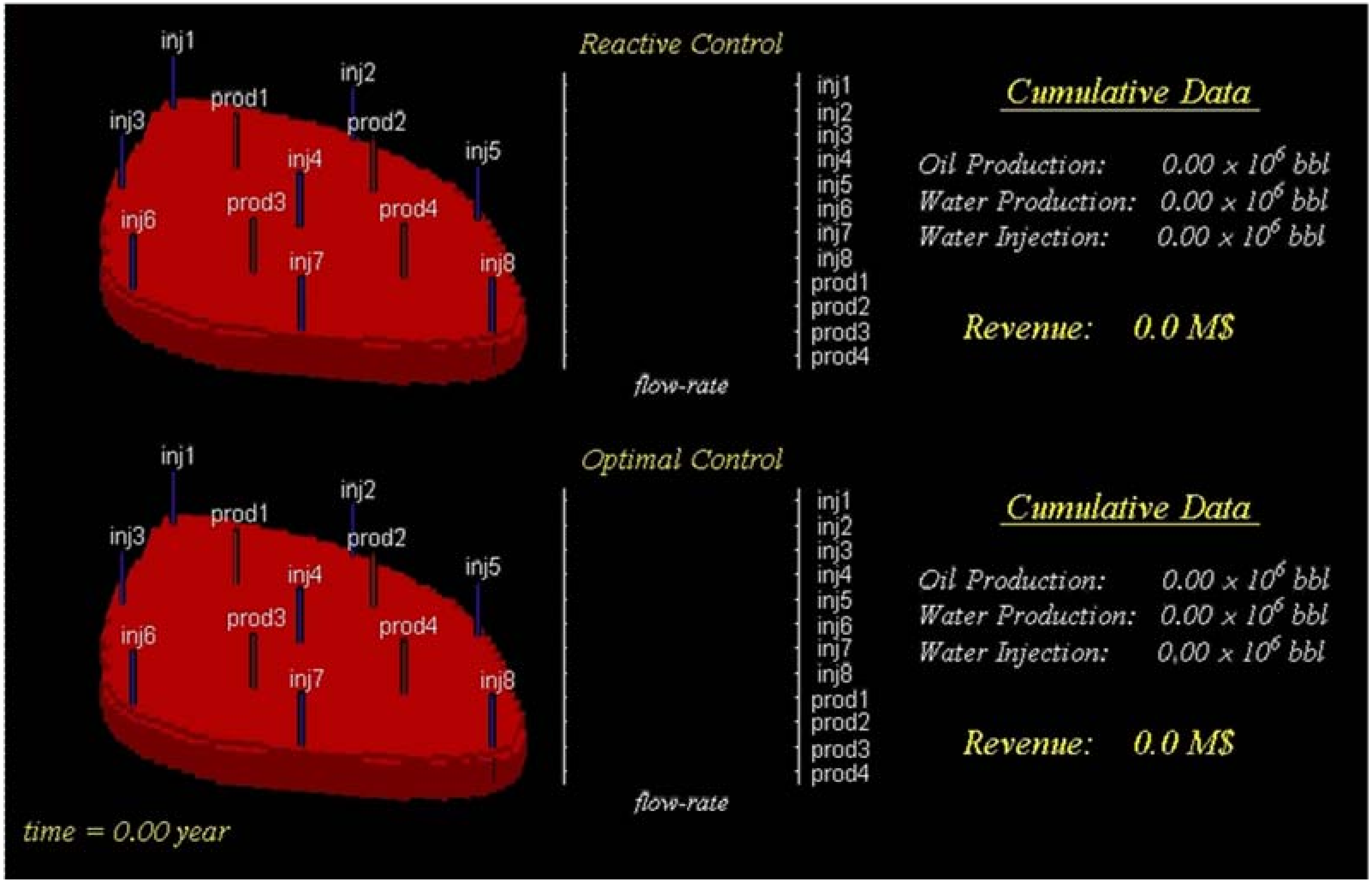


12-well example

- 3D reservoir
- 8 injection / 4 production wells
- Period of 10 years
- High-permeability channels
- 18.553 grid blocks
- Minimum rate of 0.1 *stb/d*
- Maximum rate of 400 *stb/d*
- No discount factor
- r_o = 20 *\$/stb*, r_w = 3 *\$/stb* and r_i = 1 *\$/stb*
- Optimization of economic benefit



(Gijs van Essen et al., CAA 2006)


Reactive Control
inj1
inj2
inj3
inj4
inj5
inj6
inj7
inj8
prod1
prod2
prod3
prod4
flow-rate
Cumulative Data
Oil Production: 0.00 x 10^6 bbl
Water Production: 0.00 x 10^6 bbl
Water Injection: 0.00 x 10^6 bbl
Revenue: 0.0 M$
Optimal Control
inj1
inj2
inj3
inj4
inj5
inj6
inj7
inj8
prod1
prod2
prod3
prod4
flow-rate
Cumulative Data
Oil Production: 0.00 x 10^6 bbl
Water Production: 0.00 x 10^6 bbl
Water Injection: 0.00 x 10^6 bbl
Revenue: 0.0 M$
time = 0.00 year

Why this wouldn't work

- Model has some simplifying assumptions
- Optimization over life-time reservoir (changing economic circumstances)
- …………

- Open-loop strategy
- We do not know the reservoir model!

Contents

- Introduction – the problem setting
- The models
- Model-based optimization
- **Closed-loop reservoir management**
- Parameter estimation and identifiability
- Additional optimization opportunities
- Prospects and conclusions

Closed-loop Reservoir Management

- Moving from (batch-wise) open-loop optimization to on-line closed-loop control
- However we need a model as a basis for e.g. a receding/shrinking horizon strategy

Obtaining a model

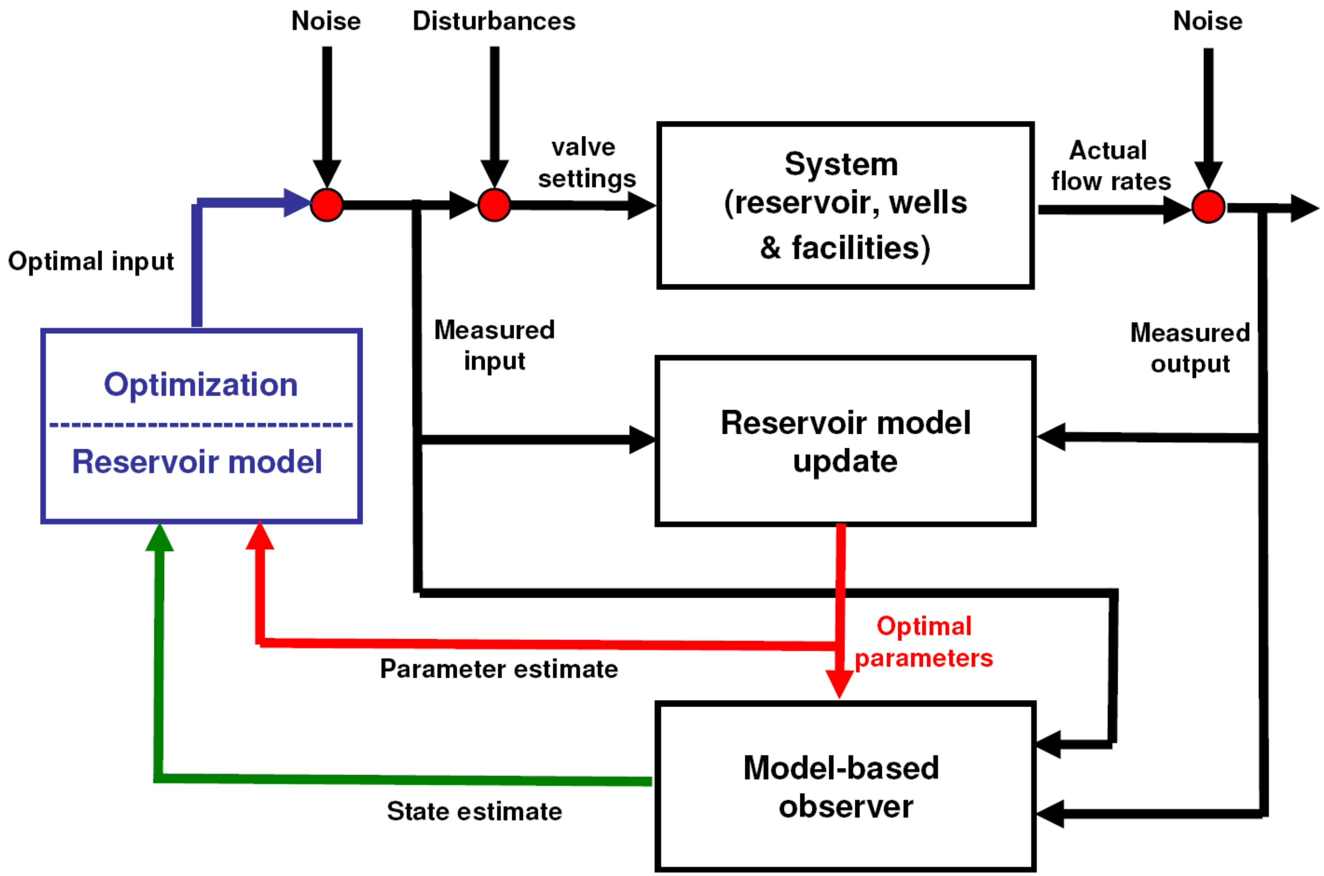
- First-principle models (geology) are very much uncertain
- Opportunities for identification are limited (nonlinear behaviour dependent on front-location, single batch process, experimental limitations)
- Option: estimate physical parameters (permeabilities) in first principles model; starting with initial guess

Closed-loop Reservoir Management

Receding/shrinking horizon control strategy:

- Use a state-estimator to reconstruct the current state
- Run the optimization algorithm to evaluate future scenario's
- Implement the optimized valve settings until the next state update
- This is actually a NMPC in a shrinking horizon implementation
- However no trajectory following but trajectory finding, i.e. real-time dynamic optimization (RTO)

Closed-loop Reservoir Management



TU Delft

DCSC Delft Center for Systems and Control

Closed-loop Reservoir Management

Several options for nonlinear state and parameter estimation:

Available from oceanographic domain:

Ensemble Kalman filter (EnKF) (Evensen, 2006)

- Kalman type estimator, with analytical error propagation replaced by Monte Carlo approach
  (error cov. matrix determined by processing ensemble of model realizations)
- Ability to handle model uncertainty (in some sense)
- In reservoir engineering used for estimation of states **and parameters** (history matching)

Ensemble Kalman Filter

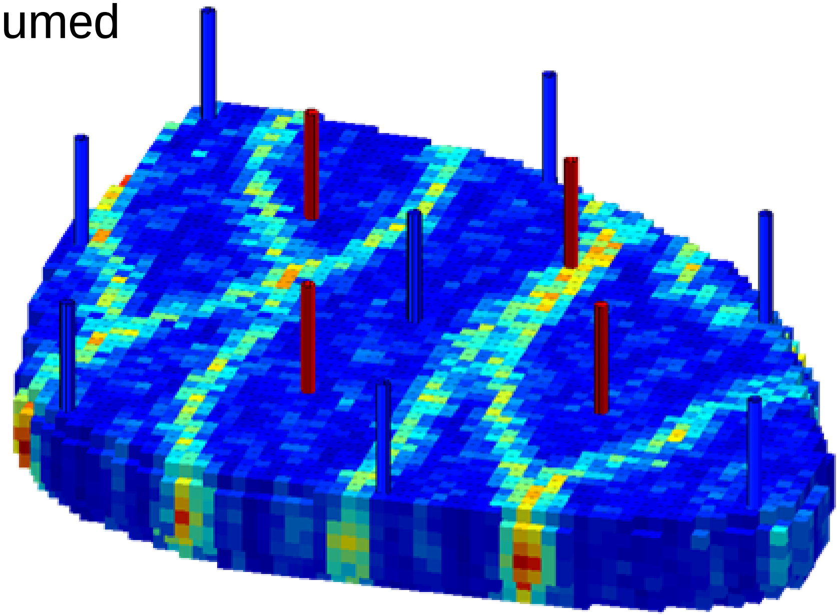
- As prior information an ensemble of initial states $\{\hat{x}_{k|k}\}$ is generated from a given distribution
- By simulating every ensemble member, corresponding ensembles $\{\hat{x}_{k+1|k}\}$ and $\{\hat{y}_{k+1|k}\}$ are generated, and stored as columns of matrices $\hat{X}$ and $\hat{Y}$ respectively
- The measurement update of a EKF is applied to every element of the ensemble, where the covariance matrices are replaced by sampled estimates on the basis of $\hat{X}$ and $\hat{Y}$.
- The update becomes: $\hat{x}_{k+1|k+1} = \hat{x}_{k+1|k} + K_{k+1}[y_{k+1} - \hat{y}_{k+1|k}]$, where K_{k+1} is given by:

$$K_{k+1} = \hat{X}\hat{Y}^T \cdot [\hat{Y}\hat{Y}^T + R]^{-1} \quad \text{(BLUE)}$$

- The result is a new ensemble $\{\hat{x}_{k+1|k+1}\}$

Closed-loop simulation example

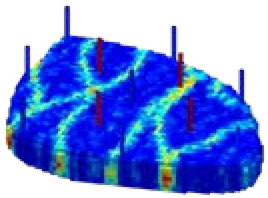
- Model with high-perm channels assumed to be 'reality'
- Permeabilities are unknown in closed-loop control
- Period of 8 years
- Objective function: NPV
  - r_o = 10 *\$/stb*, r_w = 1 *\$/stb* and r_i = 0 *\$/stb*
  - Annual discount factor: 15%
- Measurements
  - Fractional flow rates (oil/water)
  - Bottom-hole pressures
- Yearly updates of parameters and control strategy

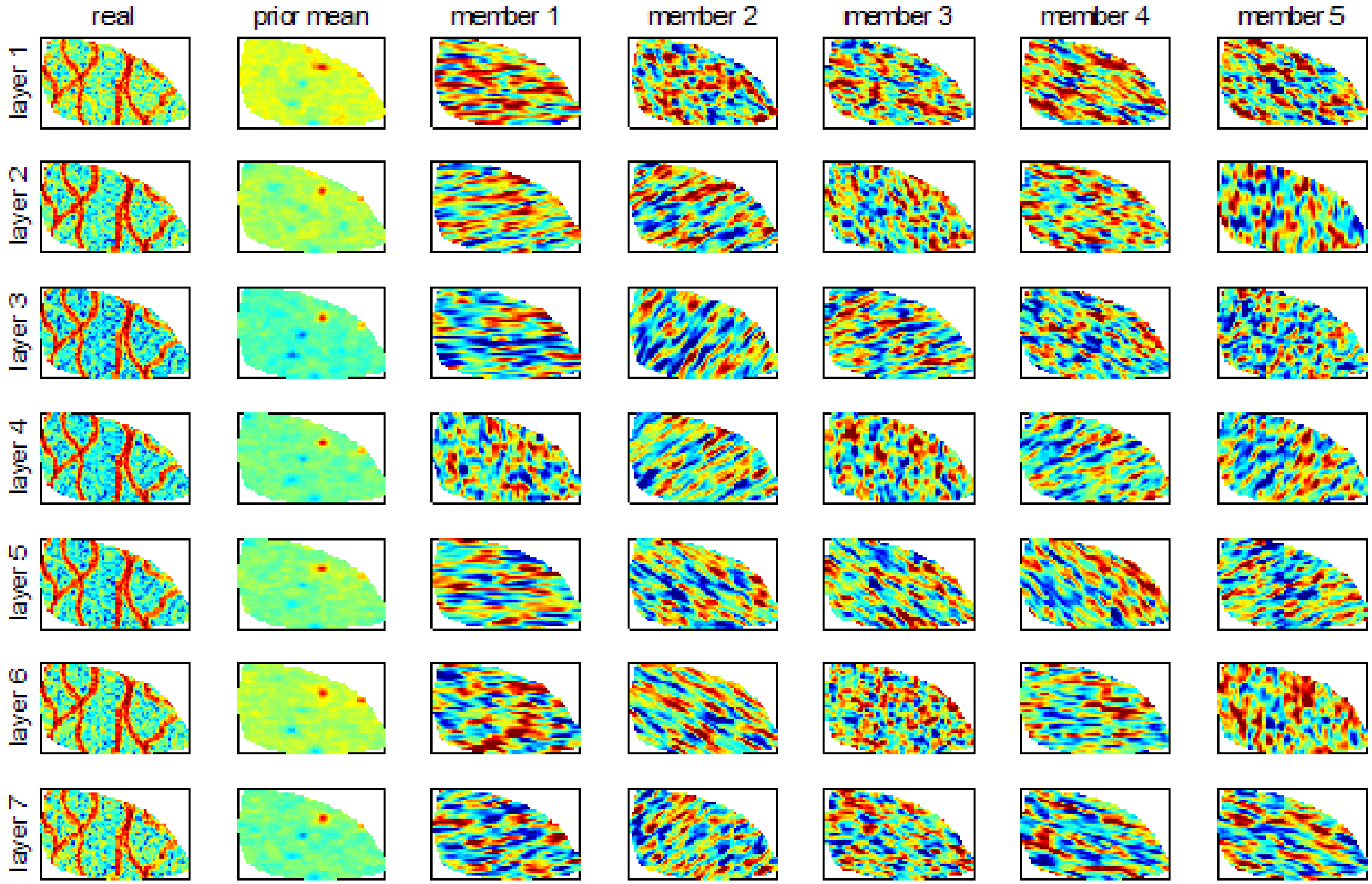


Gijs van Essen, 2006

Closed-loop simulation example

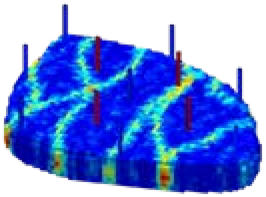
Initial ensemble

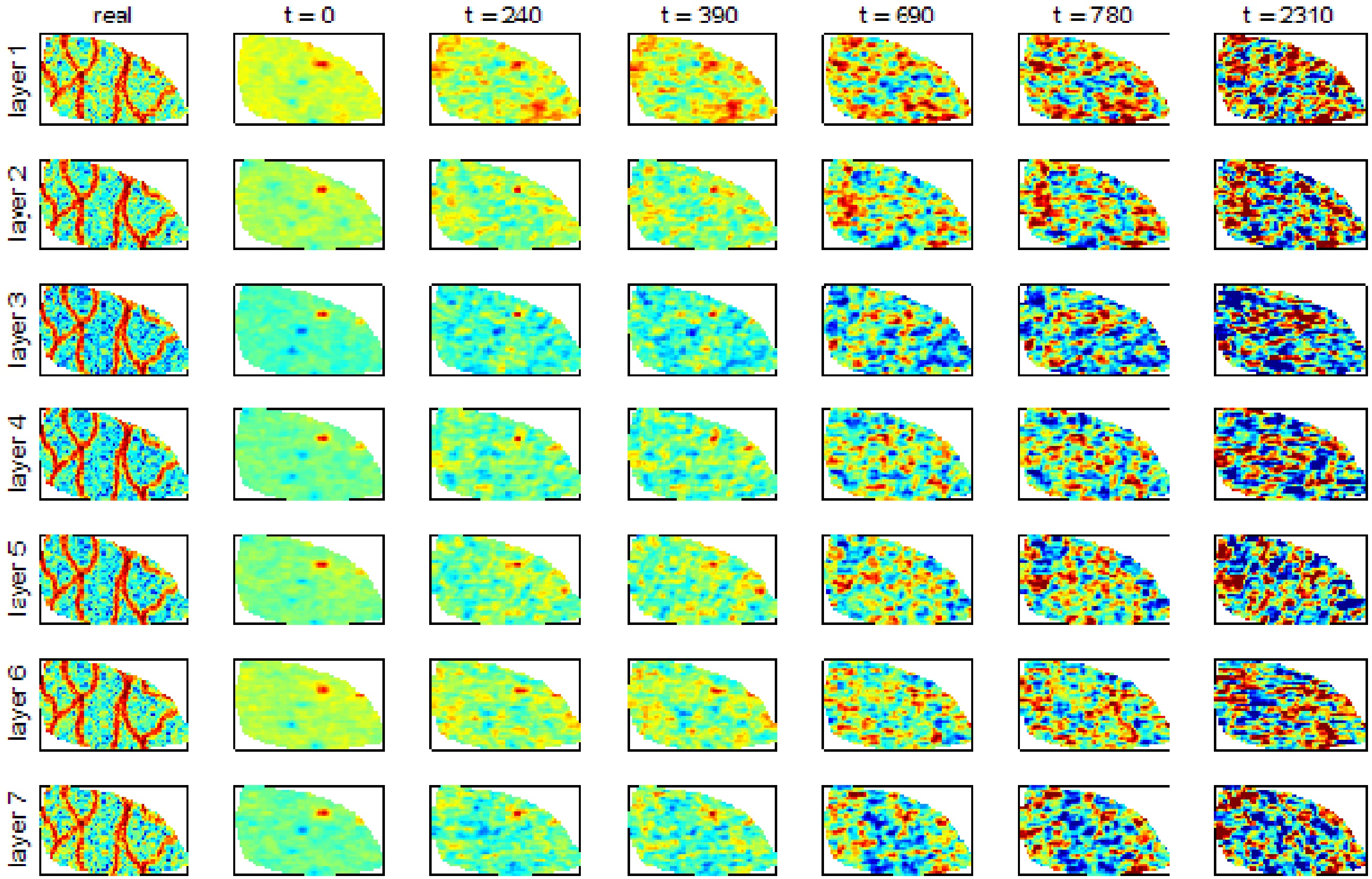




Closed-loop simulation example

Ensemble updates at different times

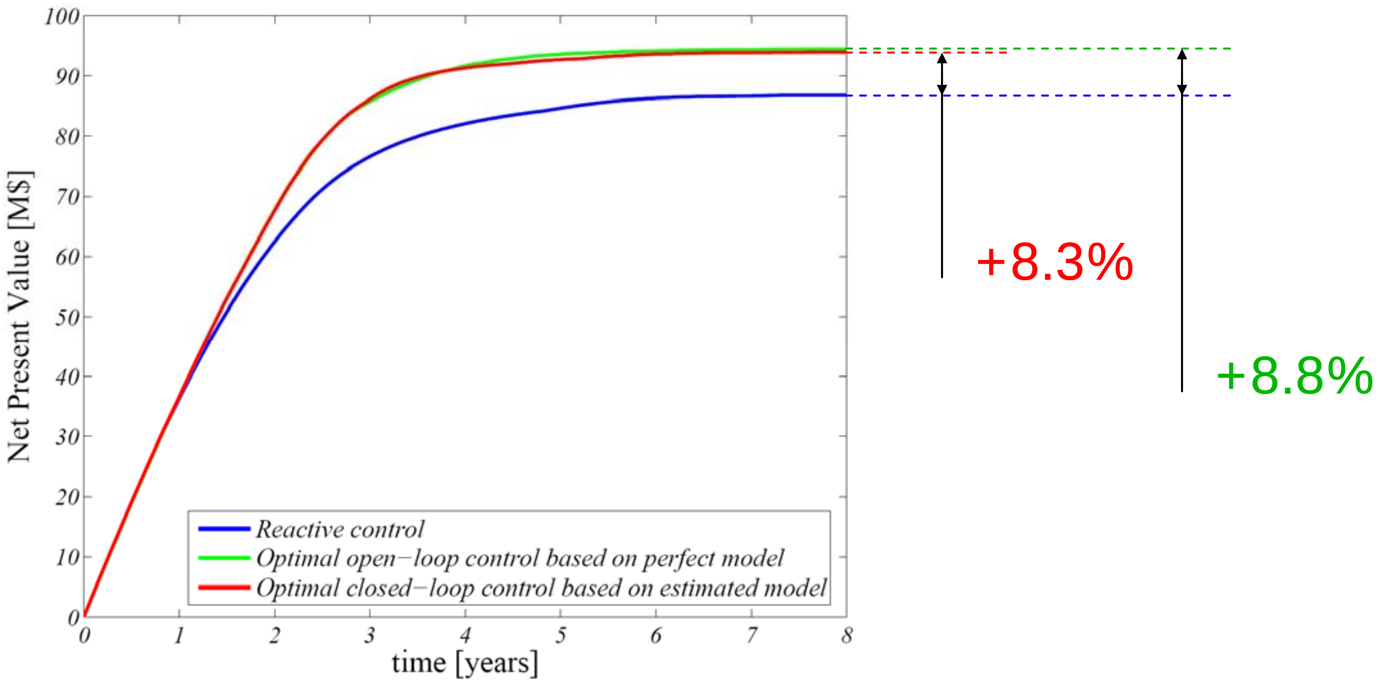




Closed-loop simulation example

Results

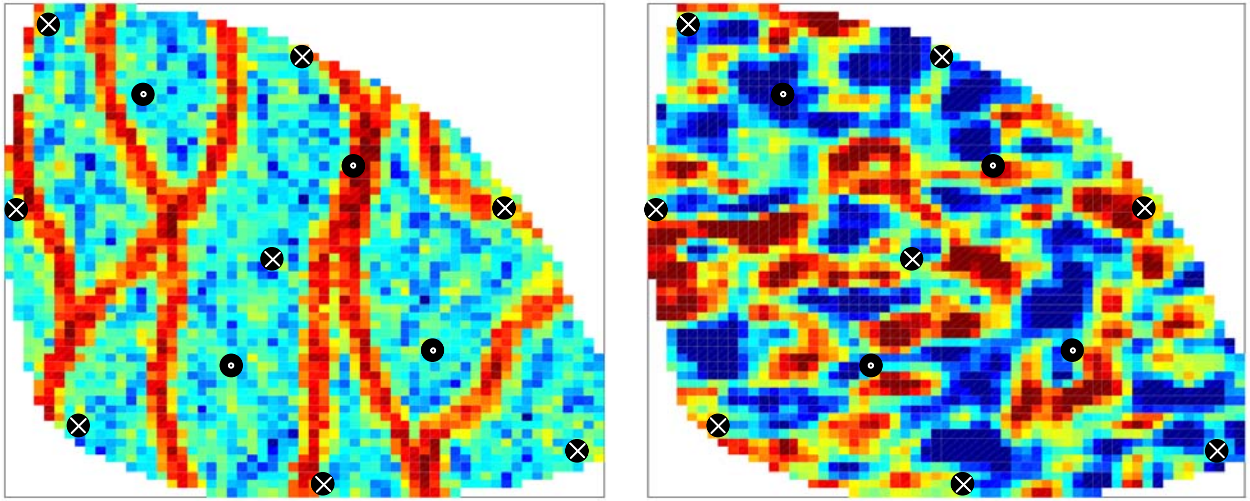
- 3 study cases: reactive control, optimal open-loop control based on perfect ('reality') model, optimal closed-loop control



Closed-loop reservoir management

Questions:

- Why are such poor models working so well?
- Does this mean that we don’t need geology?



Reservoir dynamics live in low-order space

- Observation and control in the wells
  - Models will typically be poorly observable and/or poorly controllable
  - Real (local) input-output dynamics is of limited order

- Parameter estimation:
  - Physical parameters (permeabilities) determine predictive quality but one parameter per grid block leads to excessive over-parametrization (not to be validated)

Parameter estimation and identifiability

- Through one parameter per grid block: close connection between states and parameters
- When estimating parameters (as states) in EnKF:

  - Data not sufficiently informative to estimate all parameters
  - Parameters are updated only in directions where data contains information

Result and reliability is crucially dependent on initial state/model

Parameter estimation and identifiability

- Lack of identifiability: different parameters lead to same cost function
- In sequential (Bayesian) approach to state/parameter estimation lack of identifiability is hardly observed:
- Cost function:

$$V_p(\theta) = V(\theta) + \frac{1}{2}(\theta - \theta_p)^T P_p^{-1} (\theta - \theta_p)$$
$$V(\theta) := \frac{1}{2}\epsilon(\theta)^T P_v^{-1} \epsilon(\theta), \qquad \epsilon(\theta) = \mathbf{y} - \hat{\mathbf{y}}(\theta)$$

- Analysis of $V(\theta)$ can show identifiable directions (locally)

Parameter estimation and identifiability

Option:

Calculate the identifiable subspace of the parameter domain

At a particular point $\widehat{\theta}$ the identifiable subspace of Θ can be computed! This leads to a map

$$\rho = T\theta \qquad \text{with} \qquad dim(\rho) << dim(\theta)$$

See Van Doren et al. (IFAC 2008)

Tool: analyse (svd) the matrix $\dfrac{\partial^2 V(\theta)}{\partial \theta^2} = \dfrac{\partial \widehat{\mathbf{y}}(\theta)^T}{\partial \theta} P_v^{-1} \left(\dfrac{\partial \widehat{\mathbf{y}}(\theta)^T}{\partial \theta} \right)^T,$

$$\frac{\partial \widehat{\mathbf{y}}(\theta)^T}{\partial \theta} P_v^{-\frac{1}{2}} = \begin{bmatrix} U_1 & U_2 \end{bmatrix} \begin{bmatrix} \Sigma_1 & 0 \\ 0 & \Sigma_2 \end{bmatrix} \begin{bmatrix} V_1^T \\ V_2^T \end{bmatrix} \Longrightarrow \rho = U_1^T \theta$$

Limitation: only local linearized situation can be handled

Parameter estimation and identifiability

Alternative:

Look for structural ways to come up with reduced numbers of parameters (parametrizing flow channels, etc.)

(Van Doren etal., 2009)

Contents

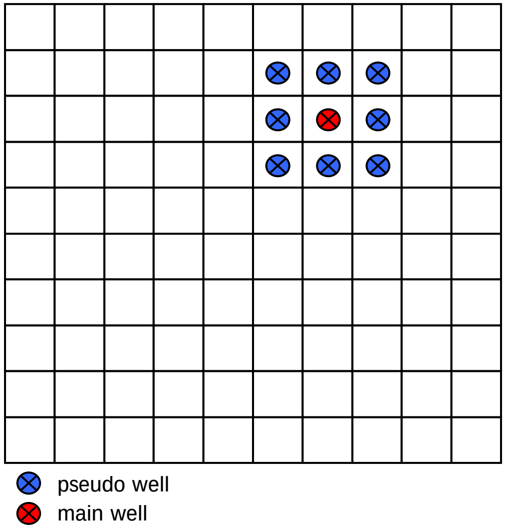
Additional optimization opportunities

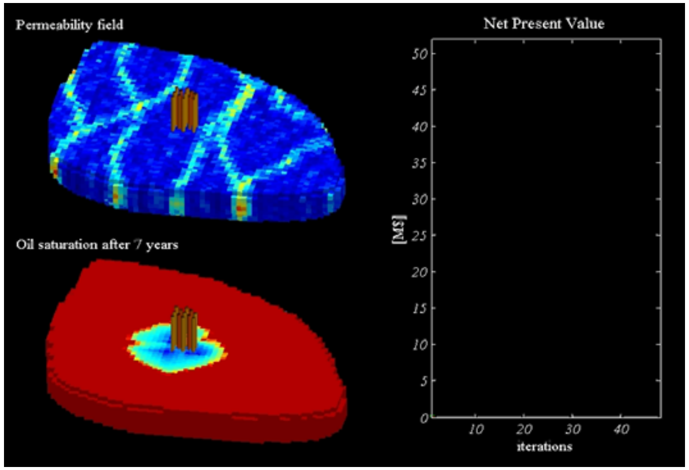
- Well location optimization
- Well design & trajectory optimization
- Robust Optimization
- Multi-objective/hierarchical optimization

Optimizing well locations

For a given model, where to place the wells?

- Only preliminary results, using gradient-based optimization, of economic cost function under production constraints





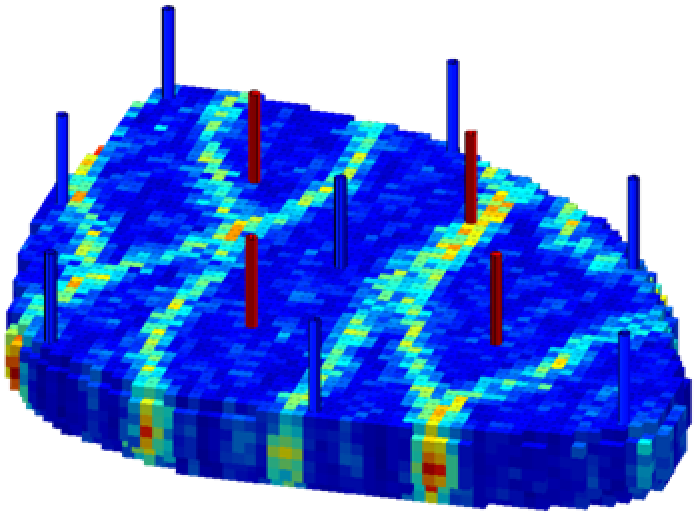
Model uncertainty / robust optimization

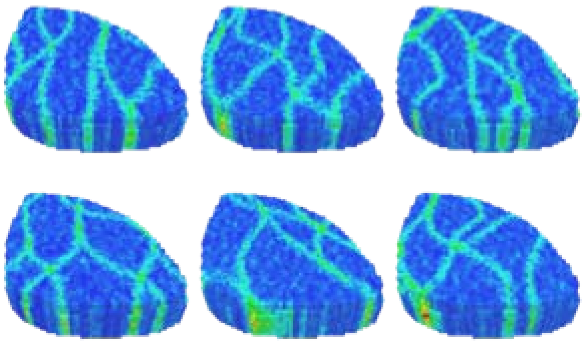
- Reservoir models / permeability structure are highly uncertain
- Option: multi-scenario / robust optimization
  based on an ensemble of potential models
- Handled in industrial practice but not in a structered way

Robust optimization example

- 3D reservoir
- 8 injection / 4 production wells
- Period of 10 years
- High-permeability channels
- Minimum rate of 0.1 *stb/d*
- Maximum rate of 400 *stb/d*
- No discount factor
- r_o = 20 *\$/stb*, r_w = 3 *\$/stb* and r_i = 1 *\$/stb*
- Optimization expectation of objective function

- *100 realizations for reservoir, 6 shown to the right*





Gijs van Essen, 2006

Robust optimization

First investigation into a robust optimization criterion over M scenarios / models:

$$\max_q \bar{J}(q) = \max_q \left(\frac{1}{M} \sum_{r=1}^{M} J_r(q) \right)$$

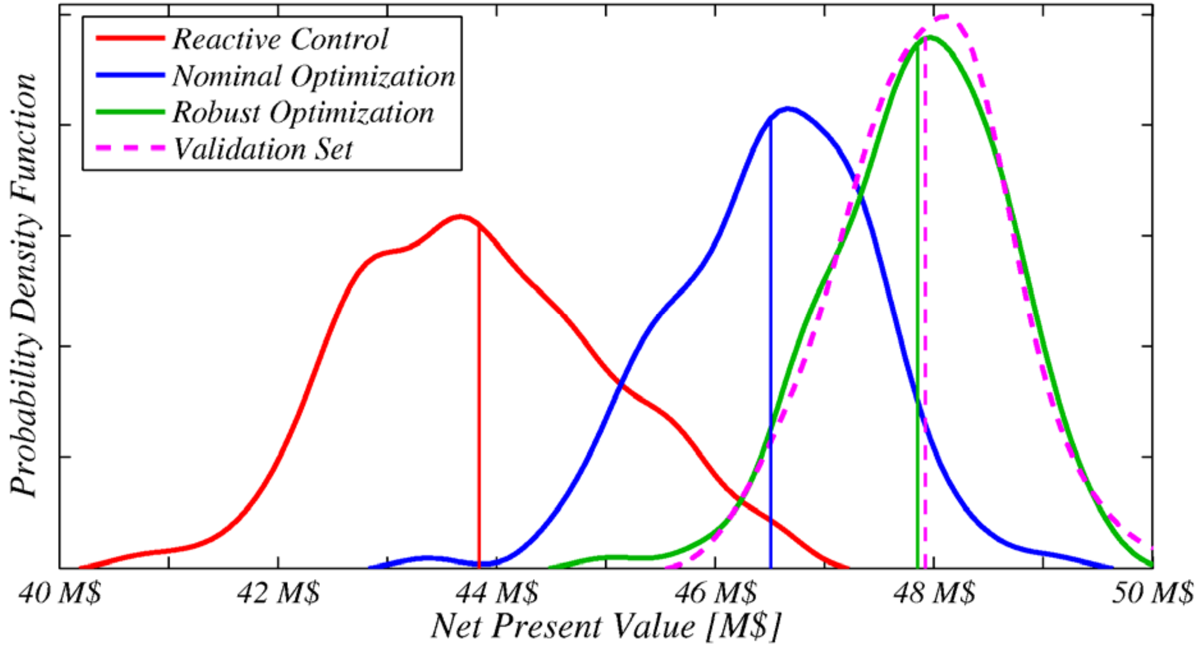
Max-mean criterion

Simulation time is extended by factor M, but still feasible; can be handled by same gradient/adjoint based approach

Robust optimization results

3 control strategies applied to set of 100 realizations:

- reactive control, nominal optimization (single model), robust optimization, verification



(Van Essen et al, CCA, 2006)

Prospects and discussion

- Hypothesis: recovery can be significantly increased by changing reservoir management from a ‘scenario-type’ to a near-continuous model-based controlled/optimized activity

- Key elements:
  - Model-based optimization under physical constraints and geological uncertainties
  - Appropriate merging of physical and measured data in low-order reliable and goal-oriented models
  - Challenging parametrization issues, in relation to controllability, observability and identifiability
  - Learning the optimal strategy in one shot (batch)

Closed-loop reservoir management

- Basic methods and tools have been set, but there remain important and challenging questions, as e.g.:
- Complexity reduction of the physical models: limit attention to the esssentials
- Structurally incorporate the role of uncertainties in modelling and optimization
- Input excitation for extra information? (learning)
- Major steps to be made to discrete-type optimization/decisions: e.g. well drilling
- Take account of all time scales (constraint handling)

Interesting challenges for systems and control!

J.D. Jansen, O.H. Bosgra and P.M.J. Van den Hof, Model-based control of multiphase flow in subsurface oil reservoirs, *Journal of Process Control*, *18,* 846-855, 2008.

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THE VALUE OF SMARTNESS

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