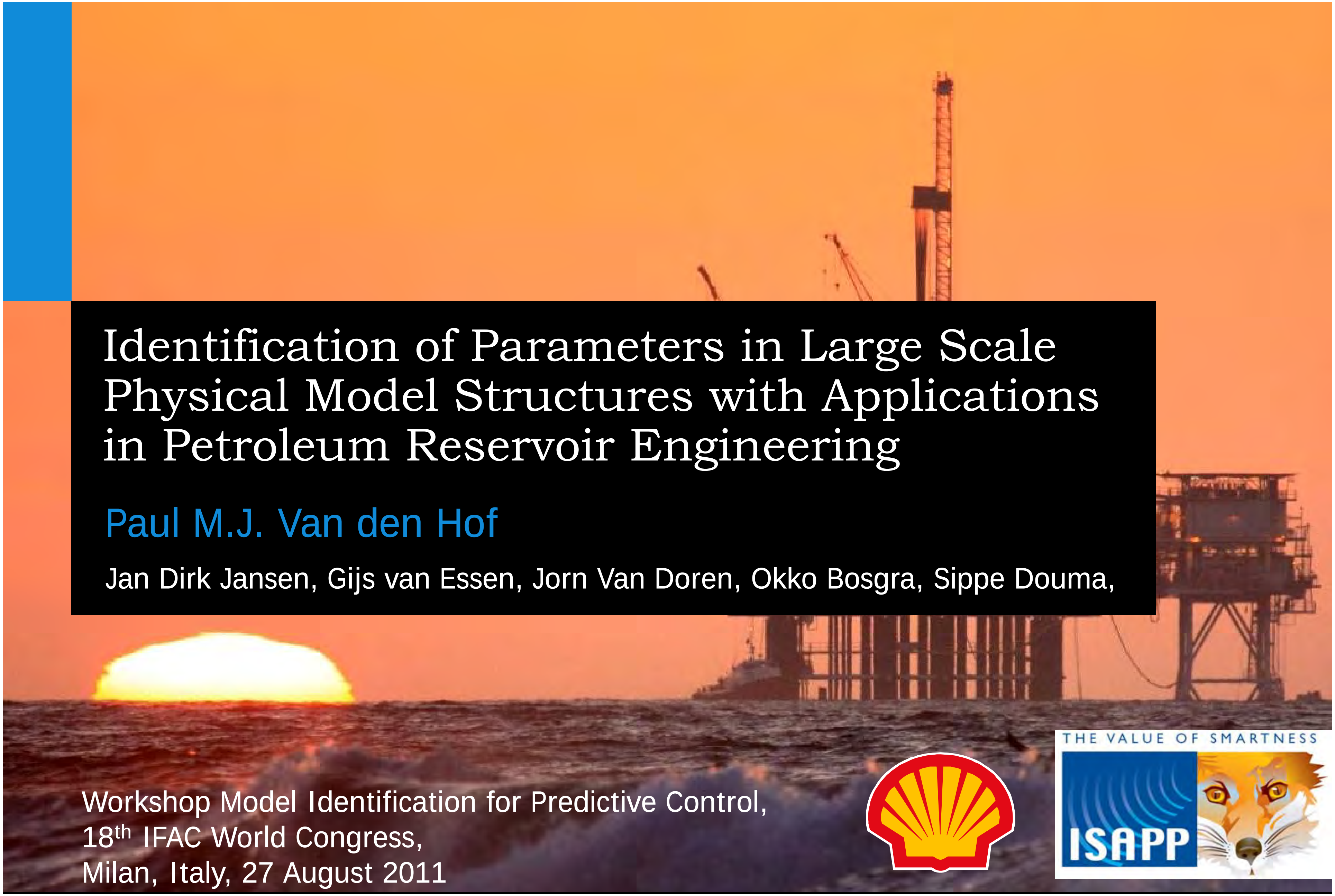


Identification of Parameters in Large Scale Physical Model Structures with Applications in Petroleum Reservoir Engineering

Paul M.J. Van den Hof

Jan Dirk Jansen, Gijs van Essen, Jorn Van Doren, Okko Bosgra, Sippe Douma,

Workshop Model Identification for Predictive Control,
18th IFAC World Congress,
Milan, Italy, 27 August 2011

THE VALUE OF SMARTNESS

ISAPP

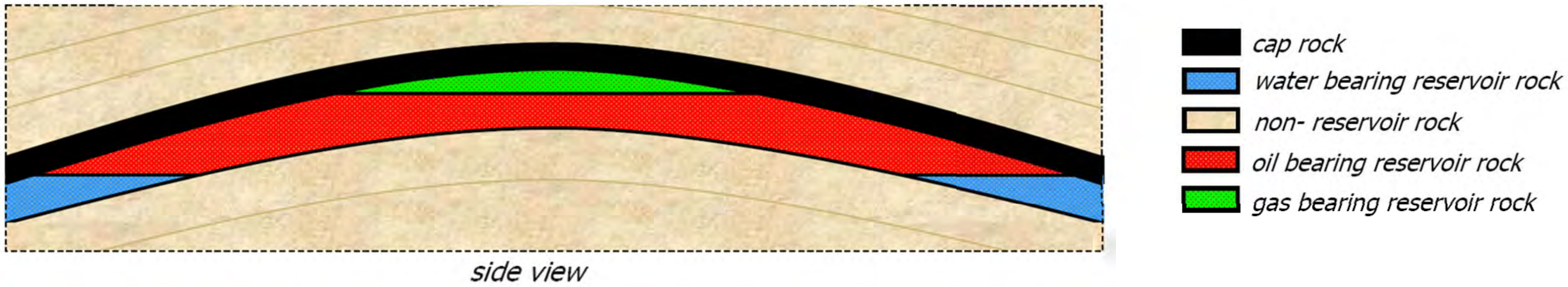
TU Delft Delft University of Technology

DCSC Delft Center for Systems and Control

Challenge the future

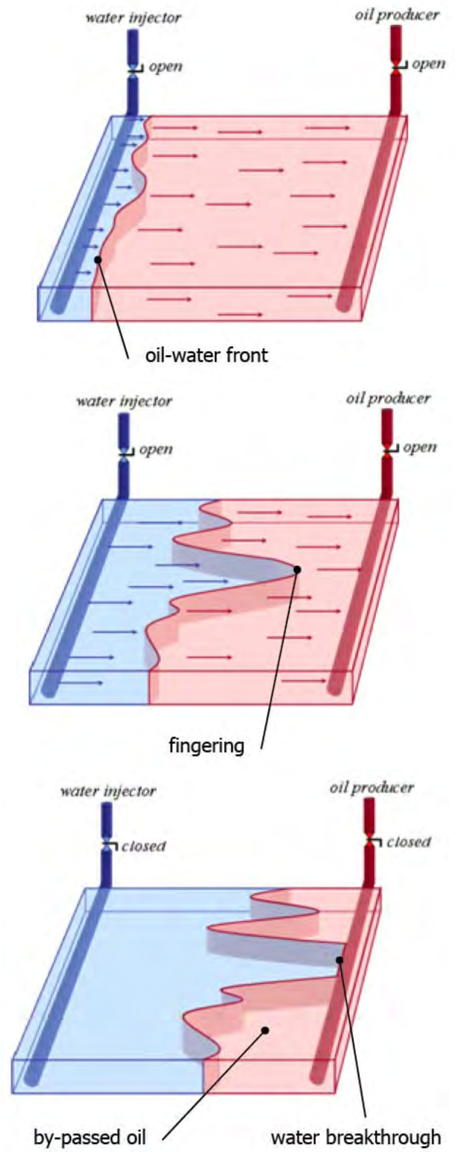
Oil Production

- Production from Oil Reservoirs
  - Porous rock with oil in pores
  - Geological structure heterogeneous
    - Very different rock properties within reservoir
  - $10^1 – 10^4$ km^2 in size
  - 10^2m – 10^4m underground
  - Difficult locations

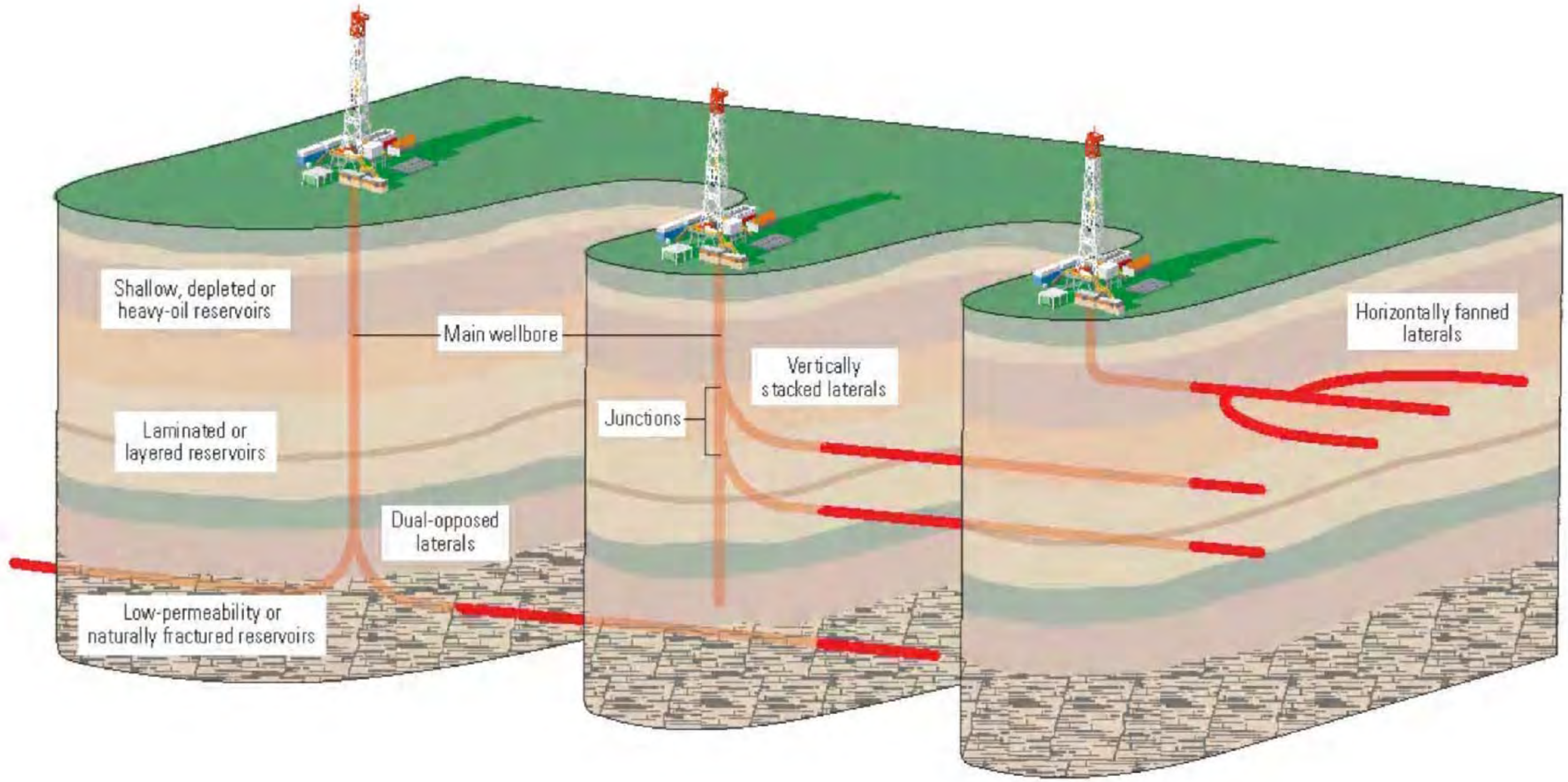


Oil Production

- Oil Production goes through multiple stages
  - Primary production (10-15%)
  - Secondary production
  - Tertiary production
- Waterflooding (WF) popular secondary production process
  - Reservoir pressure support
  - Sweeping the reservoir
- Essentially a batch process
  - Duration in the order of decades
  - 20-70% of the oil is recovered



Smart well with inflow control valves



Main question to explore:

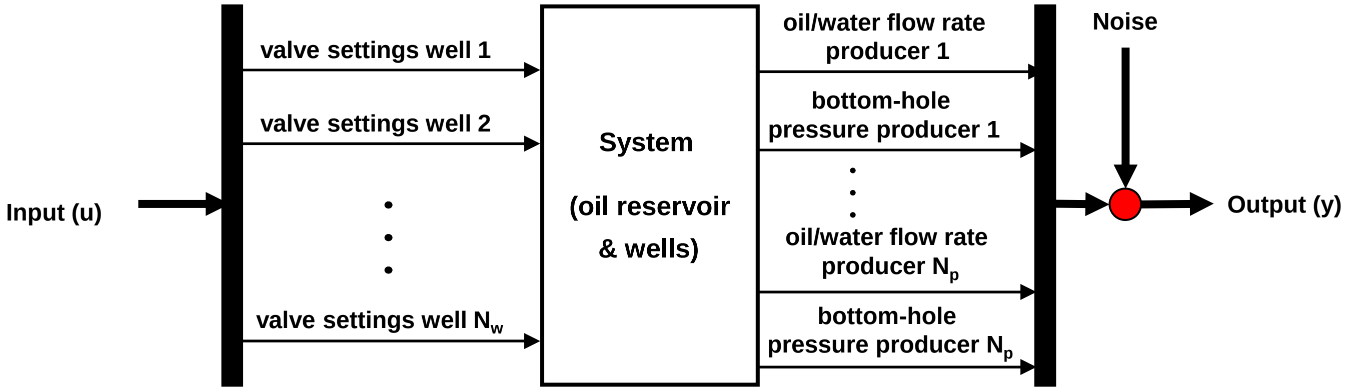
Can model-based control be of use in this field, to support the decision-making and operational strategies of the operators / field-managers ?

Contents

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:

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

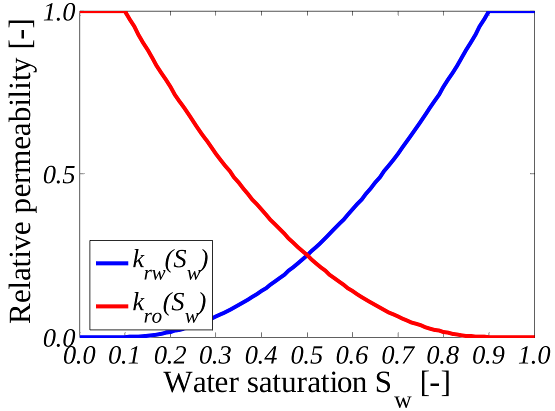
Momentum (Darcy's law):

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

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):

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

$$y_k = h(x_k)$$

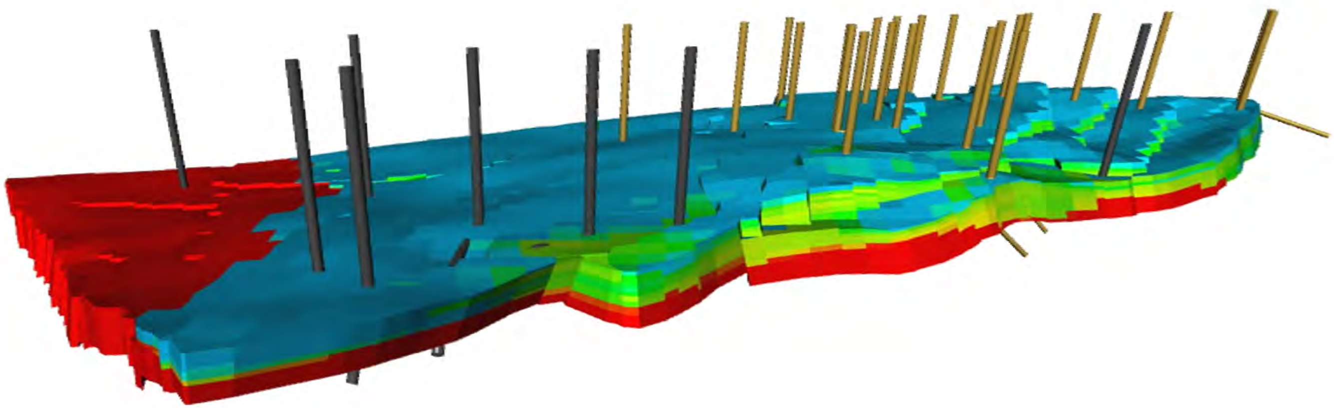
and θ typically the permeabilities in each grid block

Properties of a Reservoir Model

- Coupled pde's

- Large number of states:
  - built up out of grid blocks
  - $10^2 – 10^6$ states variables
- Long simulation times
  - Up to several hours, even days

- Highly non-linear
  - Mainly due to different fluid properties of oil & water
- MIMO
  - $10^1 – 10^2$ injection & production wells



Model-based Life-Cycle Optimization

Net present value (NPV):

- Goal: optimize economic cost function related to oil recovery, as a function of dynamic valve settings (injection and production wells)

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

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 Life-Cycle Optimization

Optimization problem:

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

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

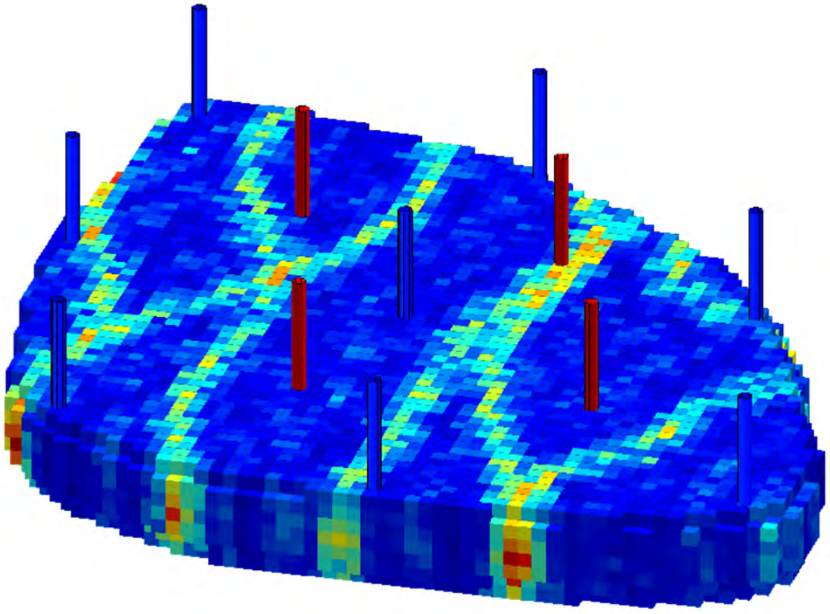
$$q_{min} \leq q_k \leq q_{max}$$

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

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)

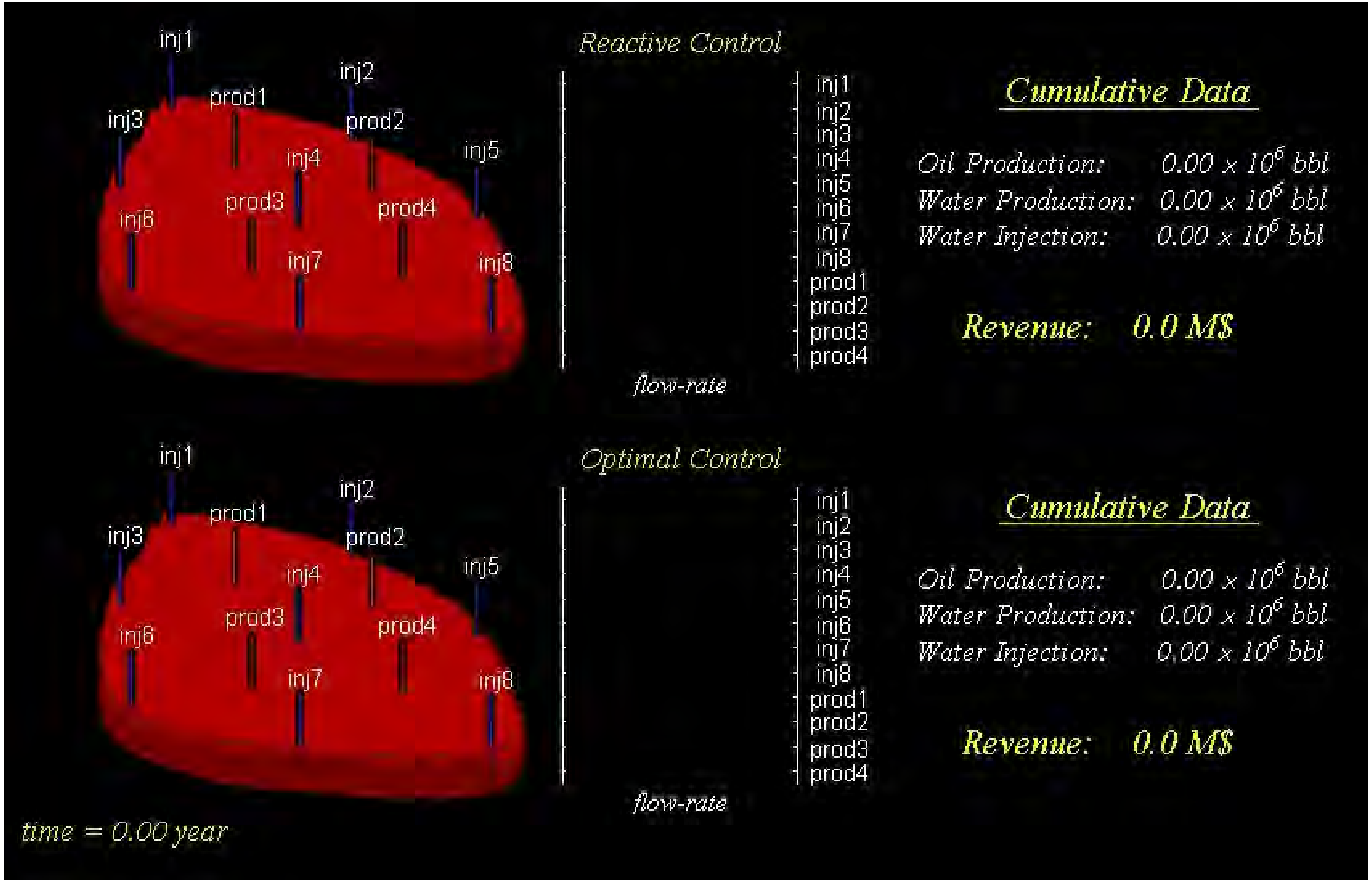
Contents

12-well example



(Gijs van Essen et al., CAA 2006)

- 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


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
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

Contents

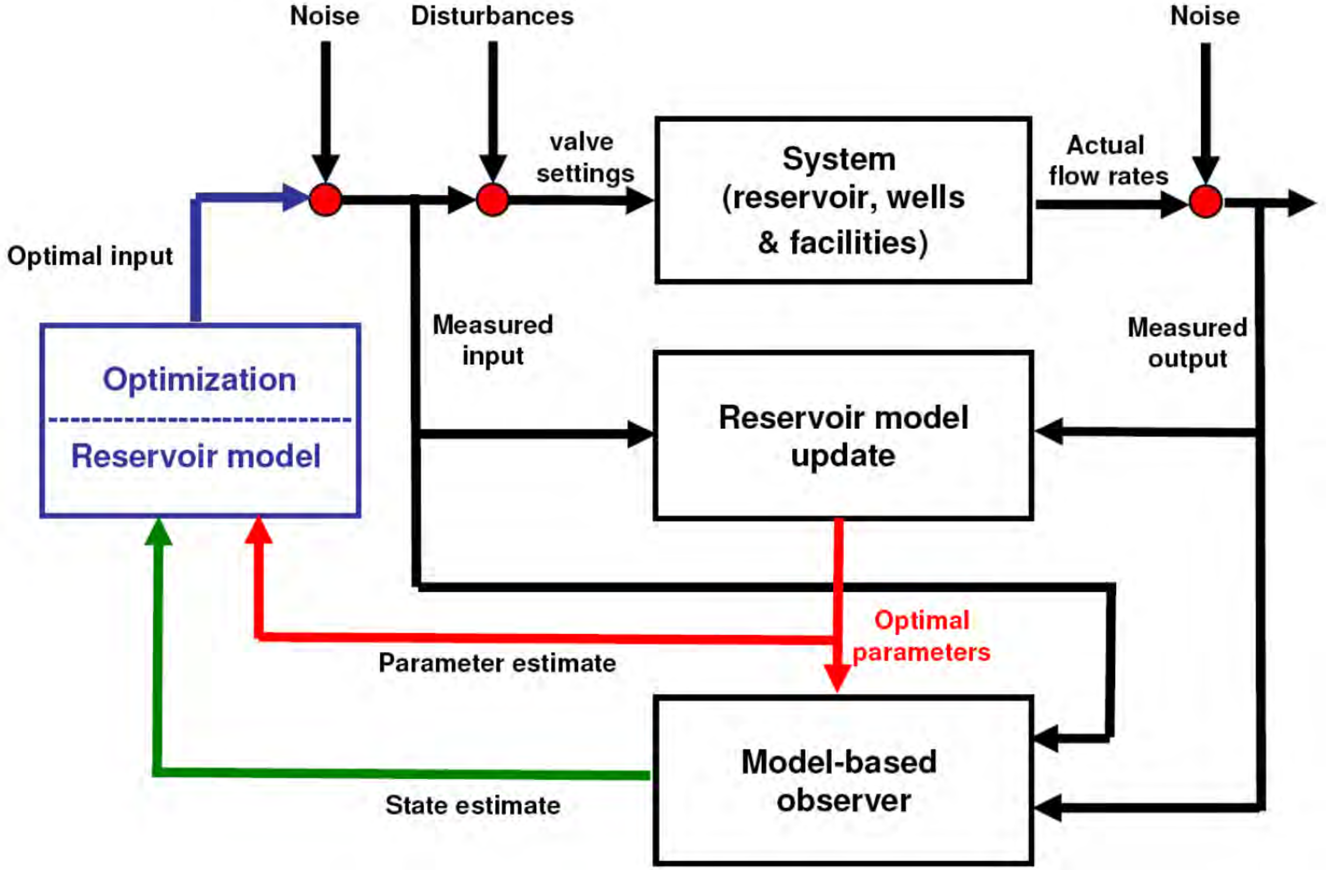
Closed-loop Reservoir Management

- 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



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

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

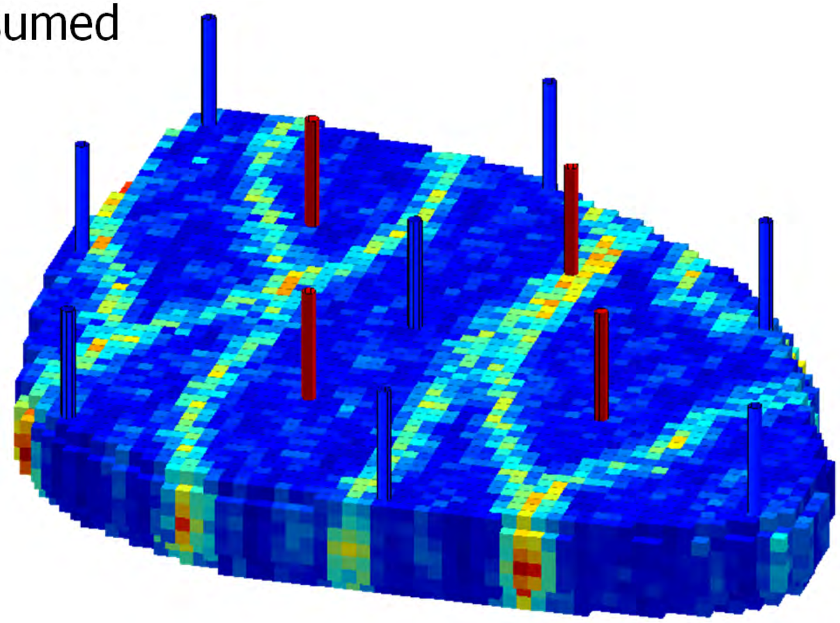
- As prior information an ensemble of initial states $\{\hat{x}_{k|k}\}$ is generated from a given distribution
- By simulating every ensemble member, corresponding ensembles $\{\hat{x}_{k+1|k}\}$ and $\{\hat{y}_{k+1|k}\}$ are generated, and stored as columns of matrices $\hat{X}$ and $\hat{Y}$ respectively
- 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

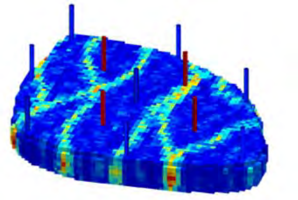
- Model with high-perm channels assumed to be 'reality'
- Permeabilities are unknown in closed-loop control
- Period of 8 years
- Objective function: NPV
  - r_o = 10 *\$/stb*, r_w = 1 *\$/stb* and r_i = 0 *\$/stb*
  - Annual discount factor: 15%
- Measurements
  - Fractional flow rates (oil/water)
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

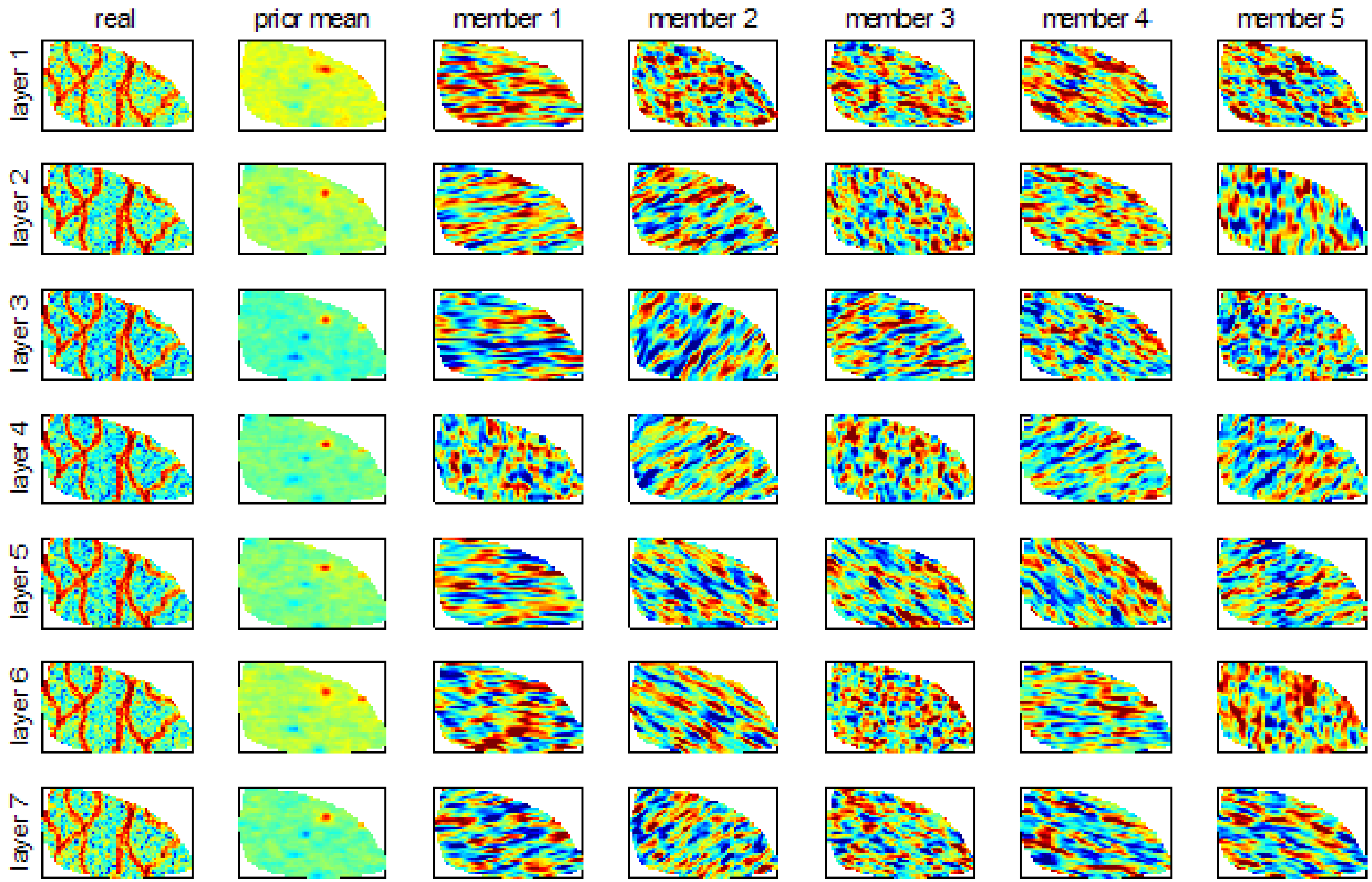


Gijs van Essen, 2006

Closed-loop simulation example

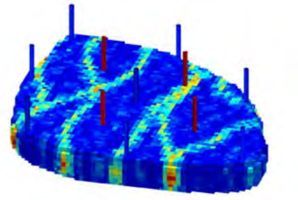
Initial ensemble

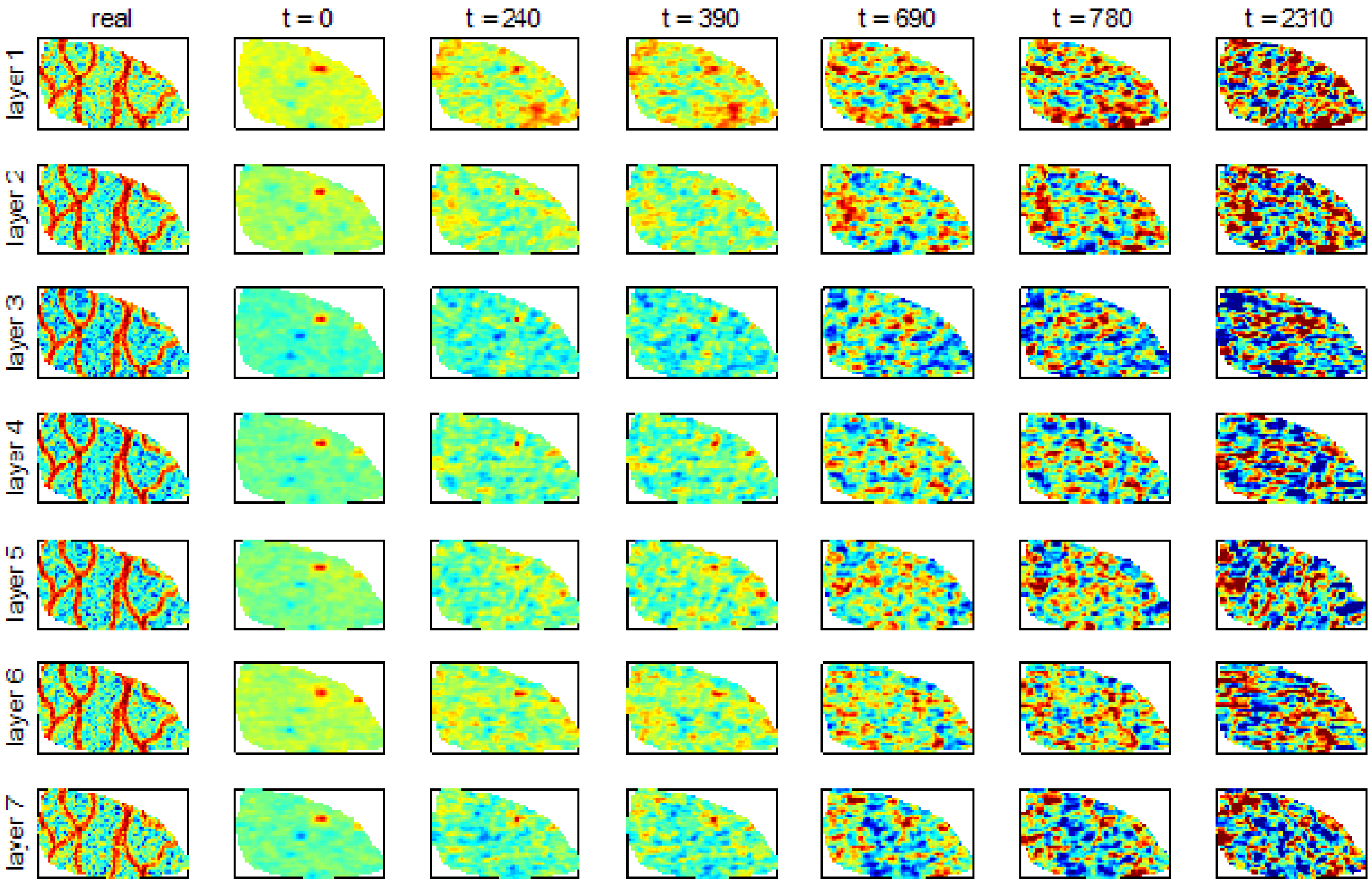




Closed-loop simulation example

Ensemble updates at different times

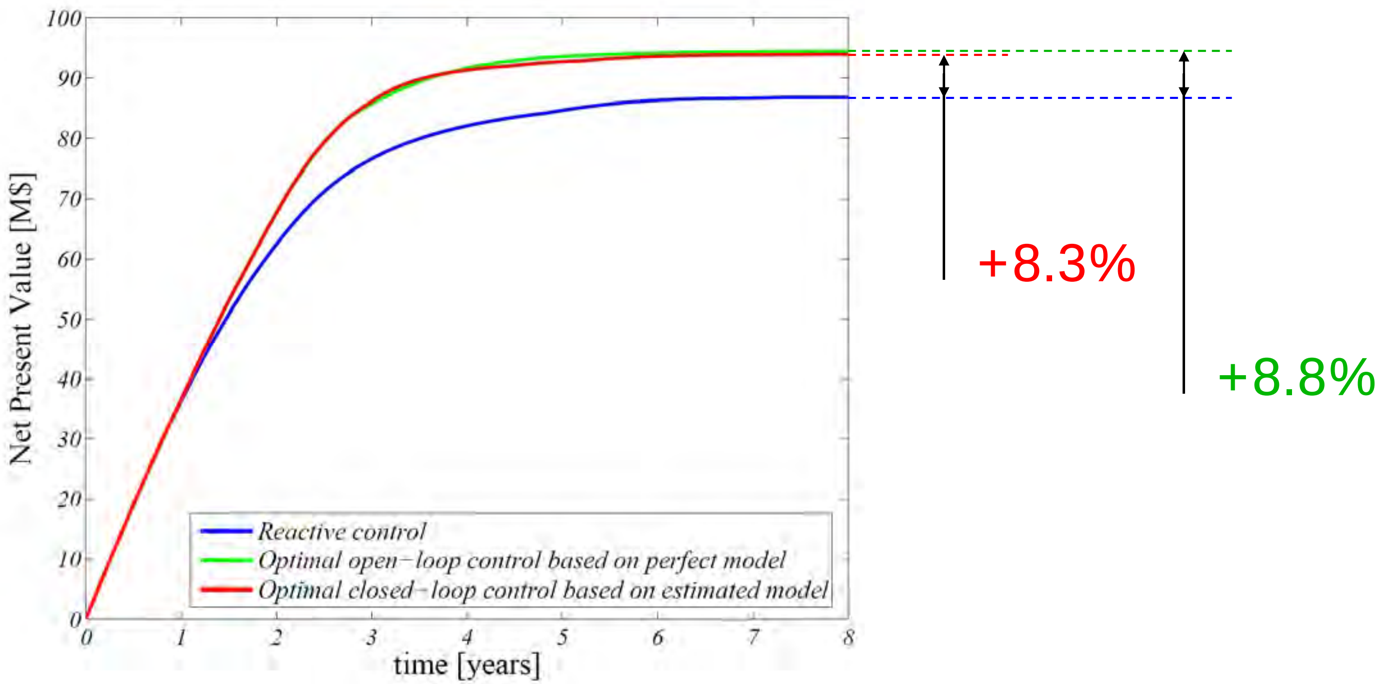




Closed-loop simulation example

Results

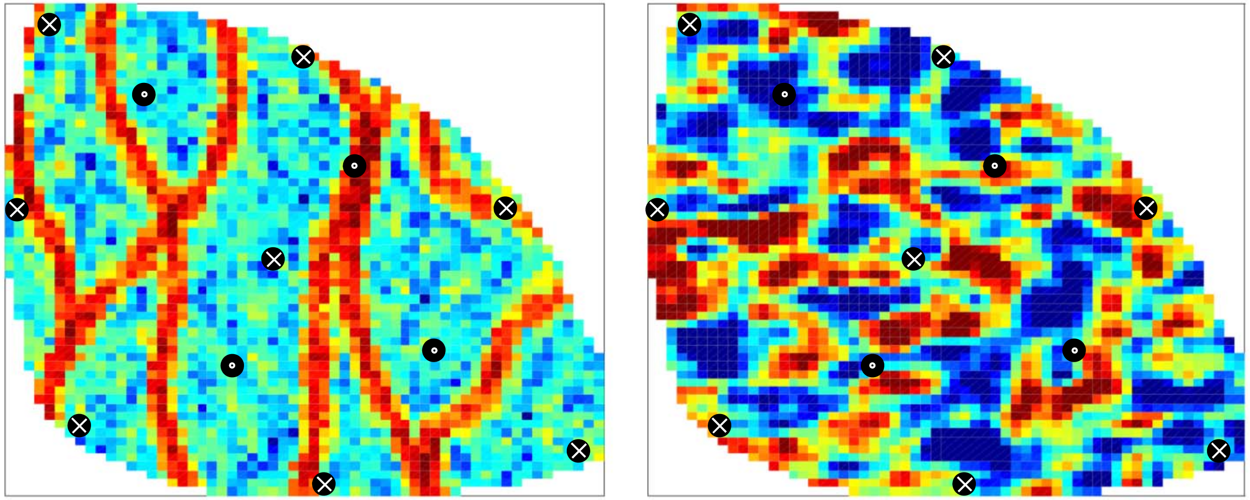
- 3 study cases: reactive control, optimal open-loop control based on perfect ('reality') model, optimal closed-loop control



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)

Contents

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:

$$V_p(\theta) = V(\theta) + \frac{1}{2}(\theta - \theta_p)^T P_p^{-1}(\theta - \theta_p)$$

$$V(\theta) := \frac{1}{2}\epsilon(\theta)^T P_v^{-1}\epsilon(\theta), \qquad \epsilon(\theta) = \mathbf{y} - \widehat{\mathbf{y}}(\theta)$$

- 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 $\hat{\theta}$ 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 $\dfrac{\partial^2 V(\theta)}{\partial \theta^2} = \dfrac{\partial \hat{\mathbf{y}}(\theta)^T}{\partial \theta} P_v^{-1} \left(\dfrac{\partial \hat{\mathbf{y}}(\theta)^T}{\partial \theta} \right)^T,$

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

Limitation: only local linearized situation can be handled

Parameter estimation and identifiability

This suggests the implementation of an iterative procedure:
Updating the reduced dimensional parametrization after every estimation step.

See Van Doren et al. (IFAC 2011, ThA25.4)

Contents

- Introduction – reservoir management
- Dynamic model and control objectives
- Optimal control example
- On-line estimation and control (closed-loop)
- Parameter estimation and identifiability
- Additional optimization opportunities
- Discussion

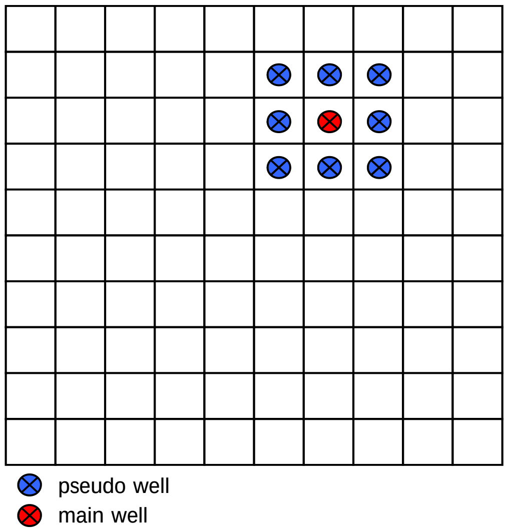
Additional optimization opportunities

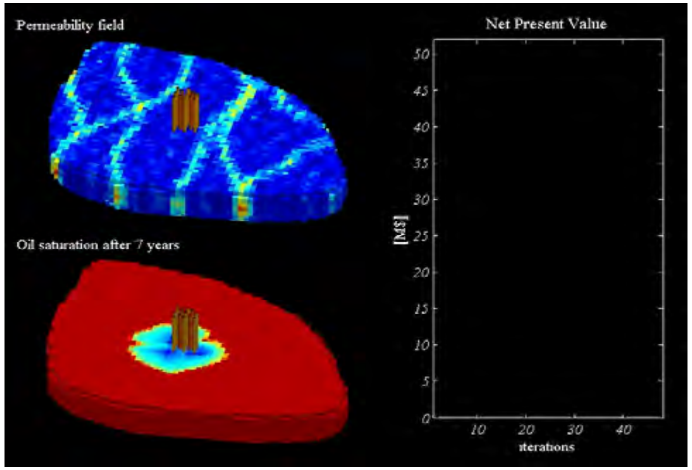
- Well location optimization
- Well design & trajectory optimization
- Robust Optimization
- Multi-objective/hierarchical optimization
  (balancing long-term and short-term objectives/actions)

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





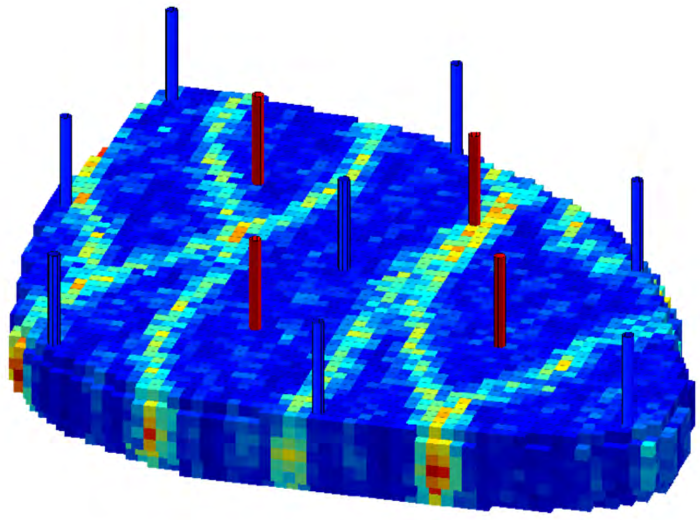
Model uncertainty / robust optimization

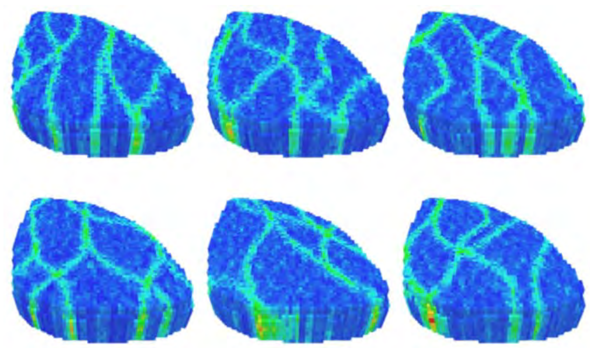
- Reservoir models / permeability structure are highly uncertain
- Option: multi-scenario / robust optimization
  based on an ensemble of potential models
- Handled in industrial practice but not in a structered way

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:

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

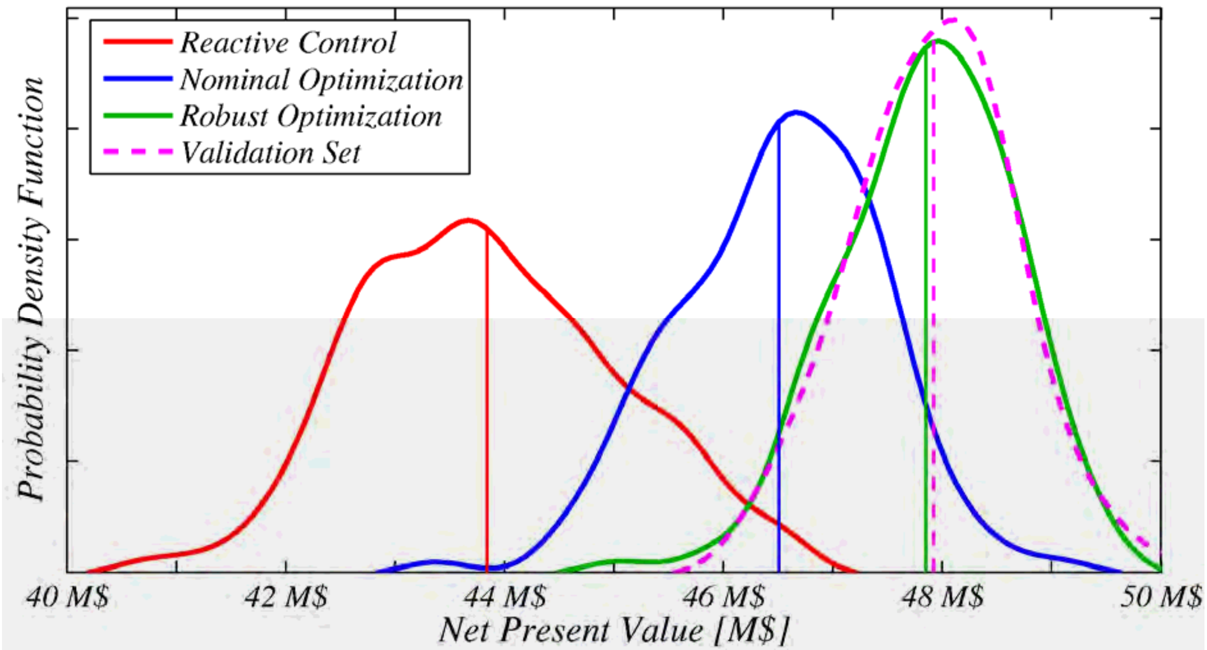
Max-mean criterion

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)

Balancing long-term/short term

Reasoning

- Optimization on the basis of nonlinear reservoir models suffers from model uncertanties
- Optimization on the basis of estimated models suffers from a lack of predictive capabilities beyond the –local- measurement interval

→ Combine the two

Extension: a two stage approach

[Van Essen, 2010]

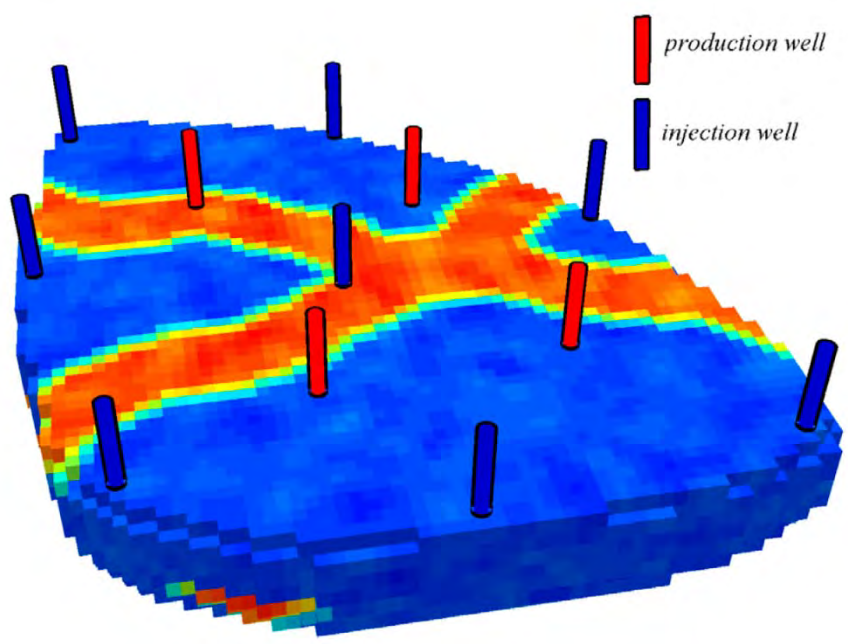
- Combine data-driven estimation of local (linear) models with tracking of long-term production targets

- Use nonlinear reservoir model (with estimated/prior chosen) grid block parameters for an (slow) ”outer loop” optimization target strategy

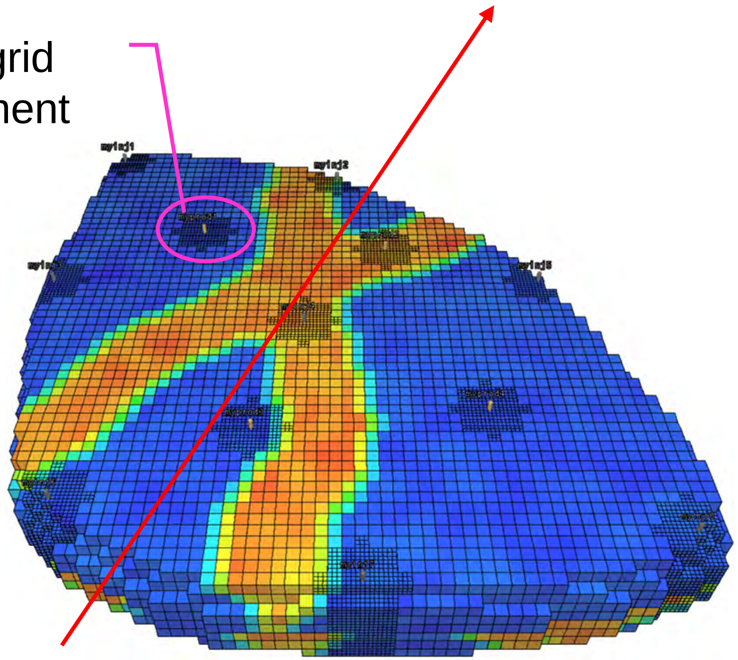
- Base short term operational decisions to follow the target strategy on a locally identified linear model, using simple black box estimation techniques, on the basis of deliberately perturbed input settings

Example: 3D reservoir

- 8 injection / 4 production wells
- High permeability channels
- Life-cycle approx. 11.5 year
- Goal: maximize NPV
- Inputs
  - Water injection rates
  - Bottom-hole pressures producers
- Outputs
  - Liquid rates producers



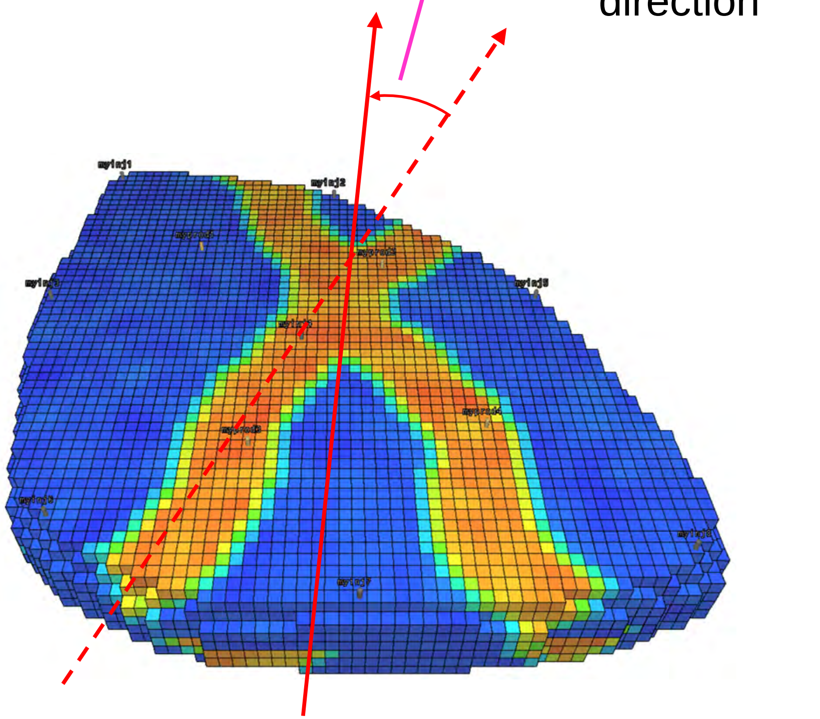
Example: 3D reservoir



‘truth’ model

time step size: 0.25 days

8 injection wells, 4 production wells



reservoir model

time step size: 30 days

Modeling error due to geological uncertainty & undermodeling of fast, local dynamics

Example: 3D reservoir

3 production strategies

1. Reactive control
   - Maximal injection rates/minimal bottom-hole pressures
   - Shut-in wells when watercut >0.90

2. Open-loop life-cycle optimization
   - Optimize inputs based on reservoir model
   - Apply to 'truth' model

3. Combined dynamic optimization & MPC control
   - Life-cycle optimization on reservoir model to obtain references
   - Excitation on 'truth' model to identify low-order model
   - MPC on 'truth' model to track references

Example: Identification Experiment

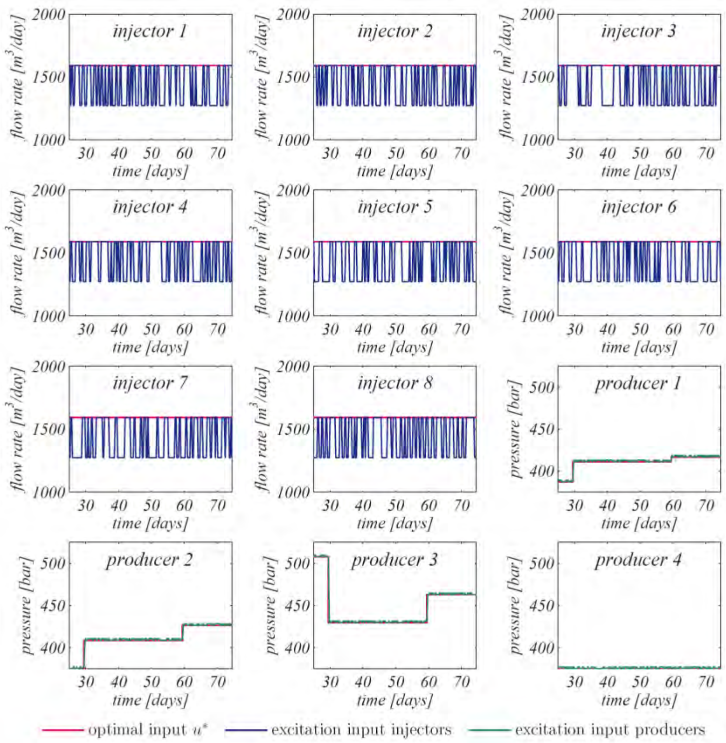
- MIMO
  - 12 inputs: 8 injection rates & 4 producer BHP's
  - 4 outputs: 4 producer liquid rates

- First 75 days of production
  - First 25 days omitted: initial reservoir conditions
  - Approximately 5x largest time constant

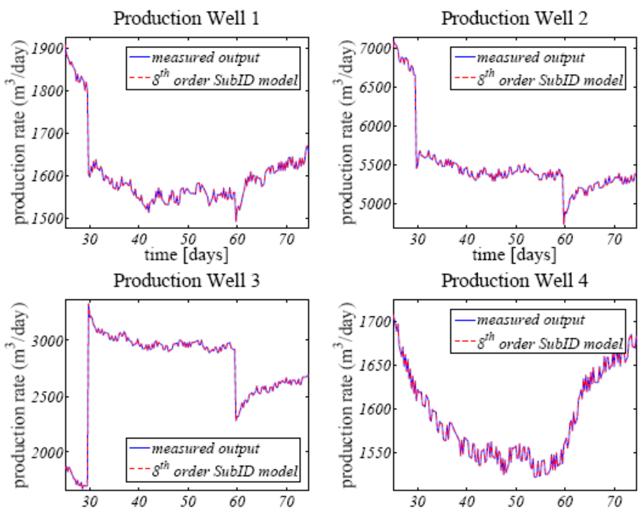
- RBS signals
  - Clock period: 3x sample time (0.25 day)
  - u^* as mean, unless limited constraints
    - Maintain good (economic) performance during experiment
  - Amplitude determined using reservoir model
    - relative contribution of injection rates and BHP's on outputs equal

Example: Identification Experiment

Input excitation for identification

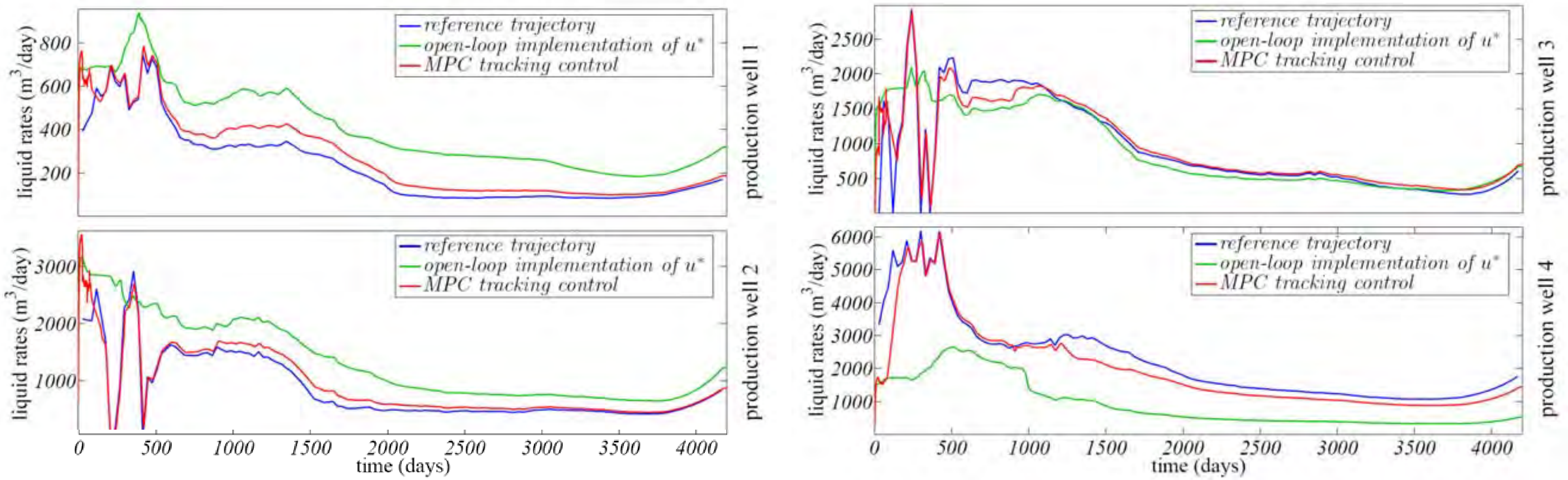


sub-space identification



Simulation fit of 8th order identified model

Example: Results



	NPV	%
Case 1: Reactive Control	550 M$	-
Case 2: Open-loop Optimization	558 M$	+1.5%
Case 3: Two-level Control	594 M$	+8.0%
Maximum based on reservoir model	596 M$	+8.4%

Discussion

- Challenging problems in model-based operation on the basis of highly uncertain information

- 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)

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.

Questions?