Model Based Control and Optimization Challenges in Reservoir Engineering

Paul Van den Hof

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

Seminar University of California, Berkeley
26 January 2011

THE VALUE OF SMARTNESS
ISAPP

TU Delft
Delft University of Technology

DCSC
Delft Center for Systems and Control

Delft University of Technology

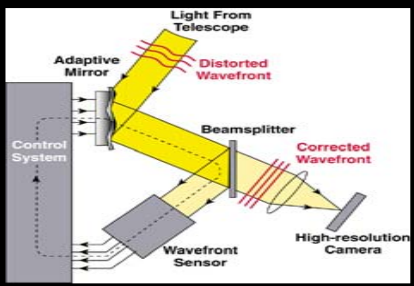
Oldest and largest of 3 Technical Universities in the Netherlands:
Delft – Eindhoven - Twente

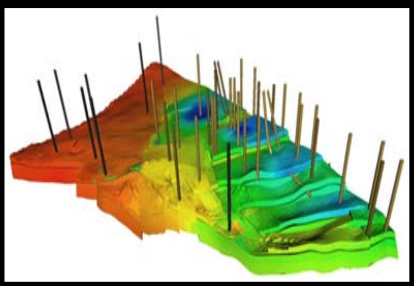
Founded in 1842 as an engineering school

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

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

Delft Center for Systems and Control




University wide center and department within Mechanical Engineering

- 14 scientific (tenured) staff
- 40 PhD students
- 15 Postdocs
- 40 MSc students / year

- BSc programs ME, EE, AP,
- MSC programs ME, EE, AP
- 3TU MSc Systems and Control
- PhD programme DISC

Delft Center for Systems and Control

- Robert Babuska
- Bart De Schutter
- Paul Van den Hof
- Michel Verhaegen
- Okko Bosgra

- Alessandro Abate
- Xavier Bombois
- Arjan den Dekker
- Peter Heuberger
- Adrie Huesman
- Tamas Keviczky
- Gabriel Lopes
- Roland Tóth
- Ton van den Boom
- Jan Willem van Wingerden

Fundamentals:

•Modelling, control and optimization of complex, non-linear and hybrid systems
•Signal analysis, signal processing and data-based modelling (identification for control)

Mechatronics and Microsystems:

- Automotive systems
- Microfactory
- AFM nano-positioning
- Smart optics systems
- Electron microscopes
- Robotics

Traffic and Transportation:

•Discrete event and hybrid systems
•Distributed multi-agent systems
•Optimal adaptive traffic control
•Advanced driver assistance systems

Sustainable Industrial Processes:

- Increase of scale in process operation
- More flexibility in operation
- Economic optimization under operating constraints
- Process intensification
- Towards model-based process management
- hydrocarbon reservoir optimization; crystallization

Areas of interest

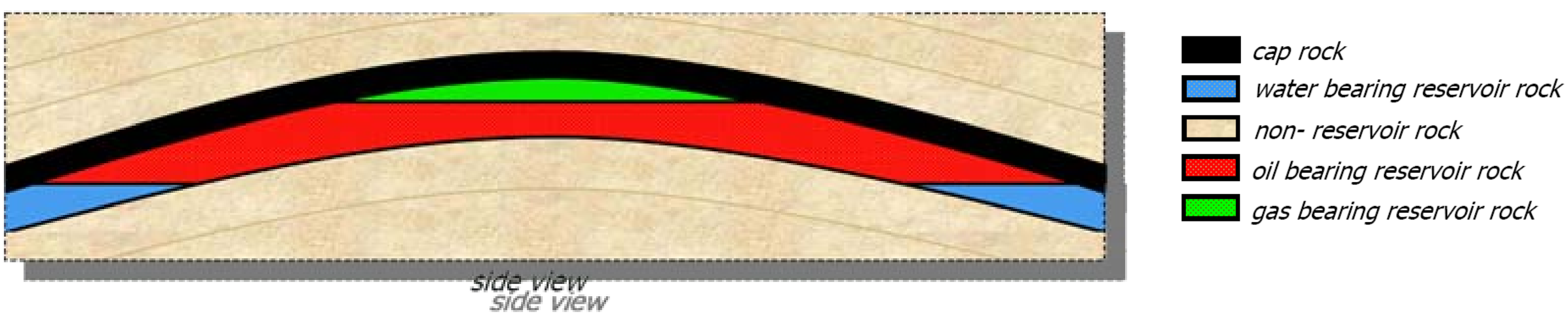
- System identification (LPV, experim.design, closed-loop, distributed)
- Autonomous model maintenance and monitoring in process control
- Nonlinear model-based control and economic optimization
- Parameter estimation in (large scale) physical structures
- Model-based measurement and control in electron microscopy

Applications

- Water flooding in reservoir engineering
- Crystallization processes
- Industrial hydrocarbon/gas-to-liquid production processes
- Intensified reaction systems (process intensification)
- Multiphase-flow systems (ILS)
- Microscopy (AFM, electron microscopes)

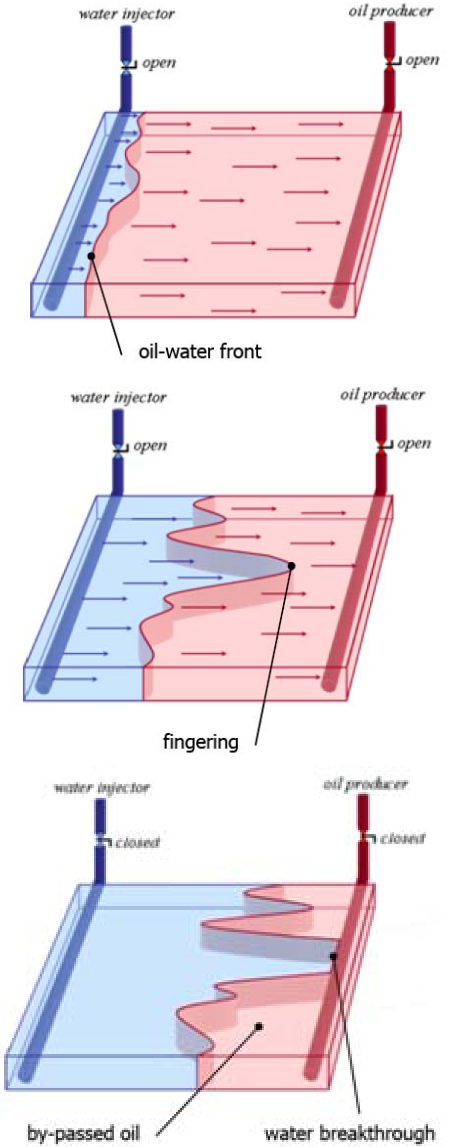
Oil Production

- 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

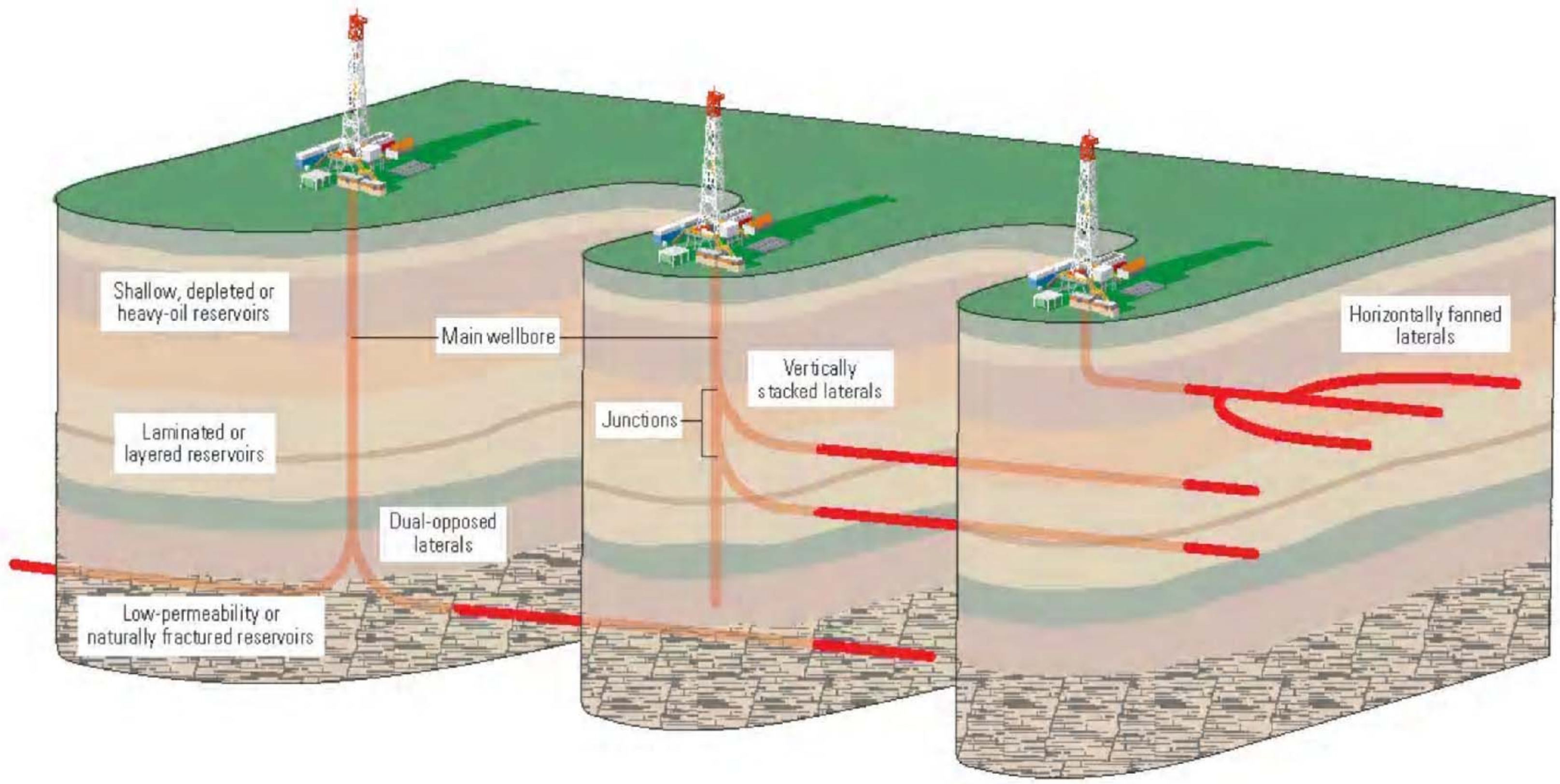


Oil Production

- Oil Production goes through multiple stages
  - Primary production
  - 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
  - On average 35% of the oil is recoved



Smart well with inflow control valves



Main question to explore:

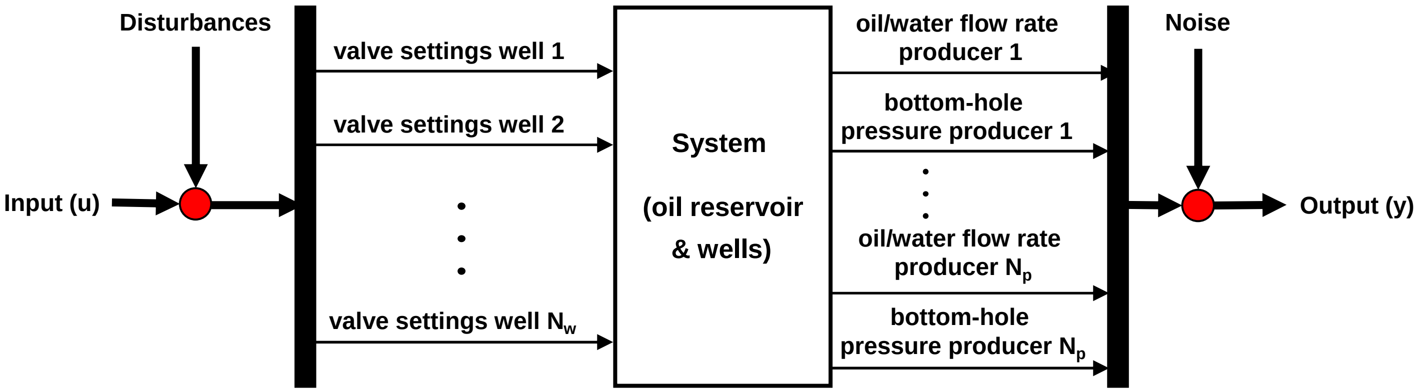
Can model-based control be of use in this field, to support the decision-making and operational strategies of the operators / field-managers ?

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:

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

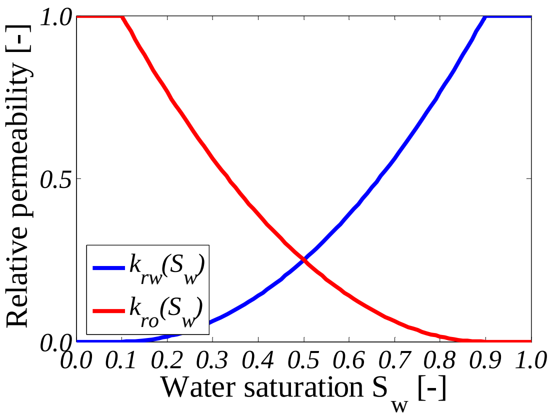
Momentum (Darcy's law):

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

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):

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

$$y_k = h(x_k)$$

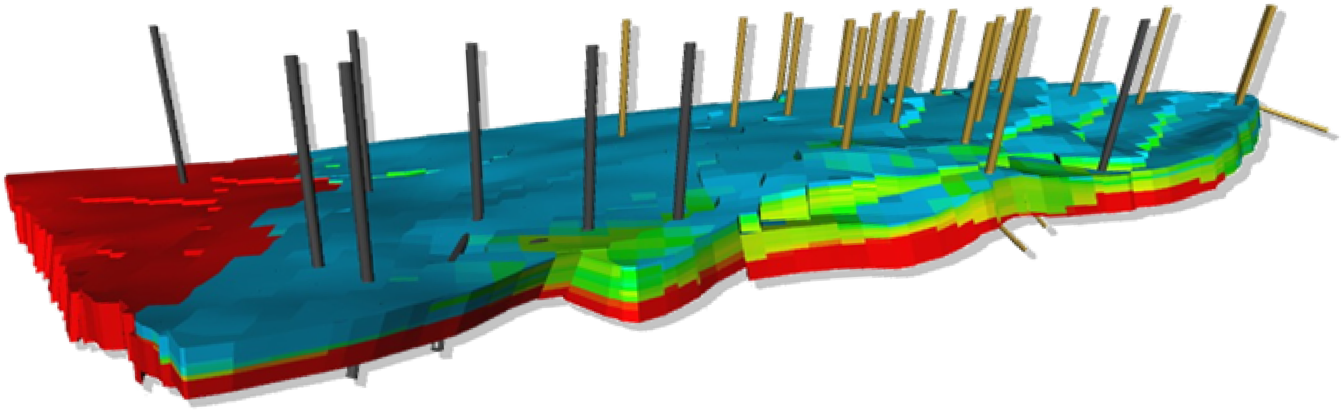
and θ typically the permeabilities in each grid block

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

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

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

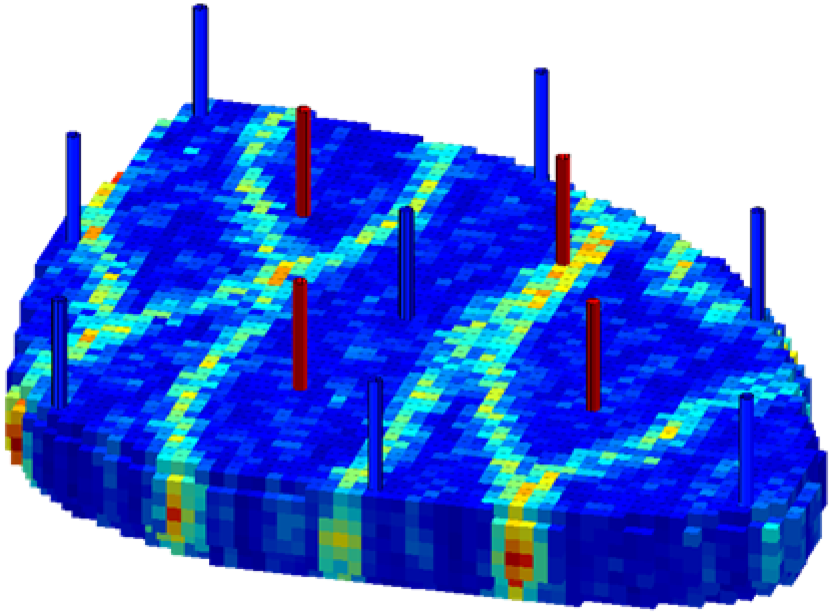
Non-convex optimization, solved by gradient-based method: Adjoint-variables calculation through backward integration of the related (Hamiltonian based adjoint) equation.
(feasible for systems of this size)

Contents

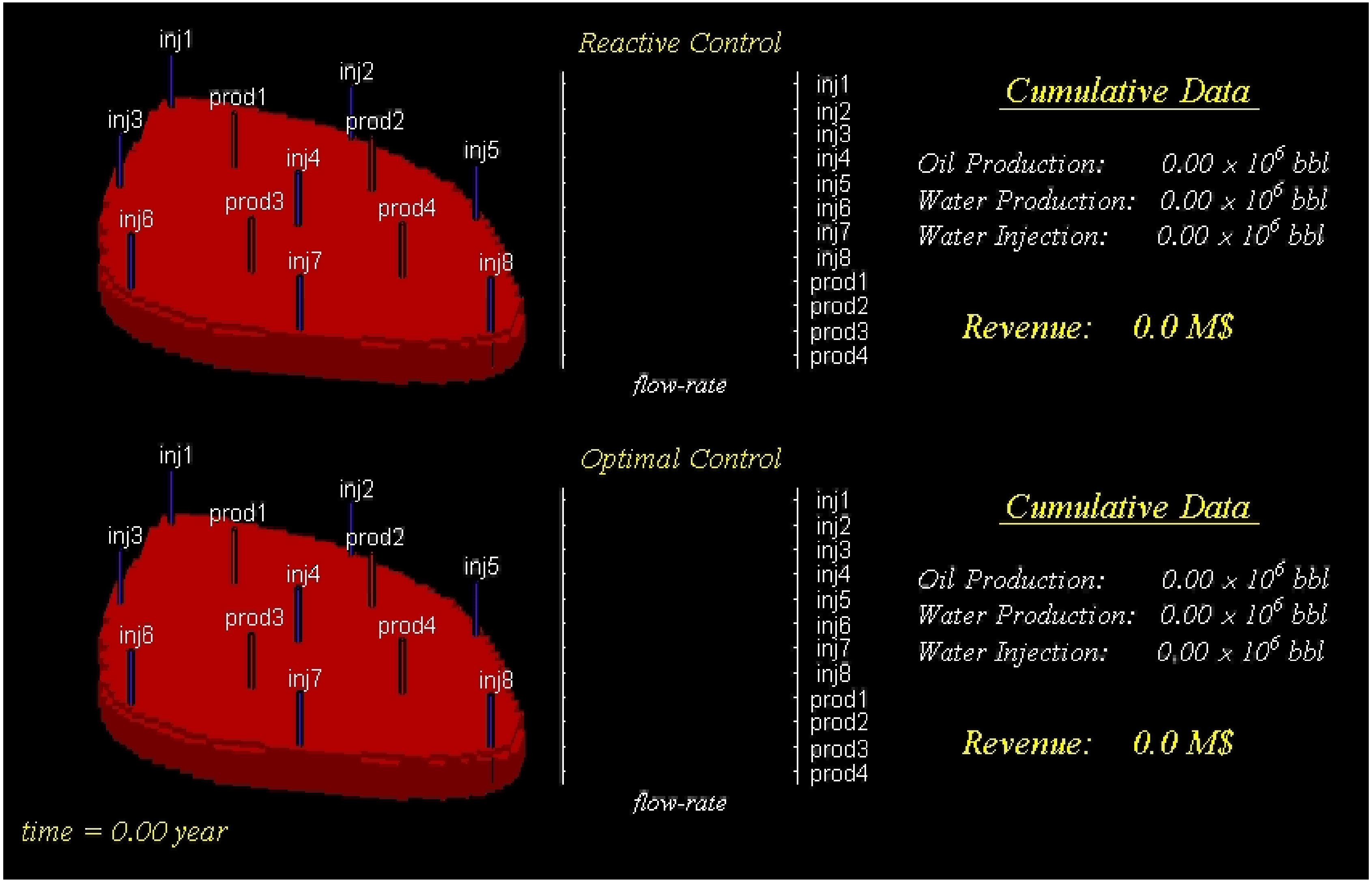
- Introduction – reservoir management
- Dynamic model and control objectives
- Optimal control example
- On-line estimation and control (closed-loop)
- Parameter estimation and identifiability
- Additional optimization opportunities
- Discussion

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

Contents

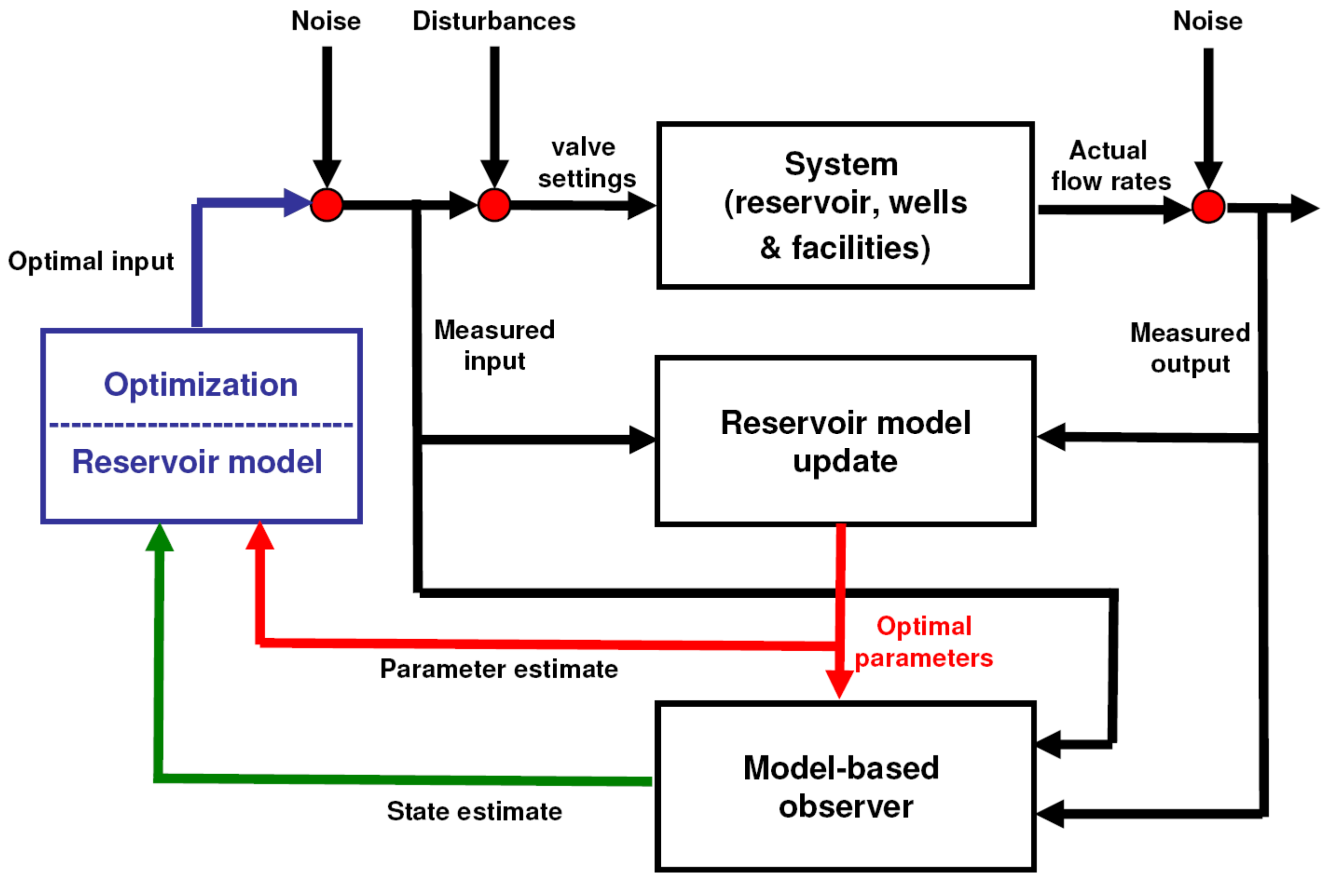
Closed-loop Reservoir Management

- 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

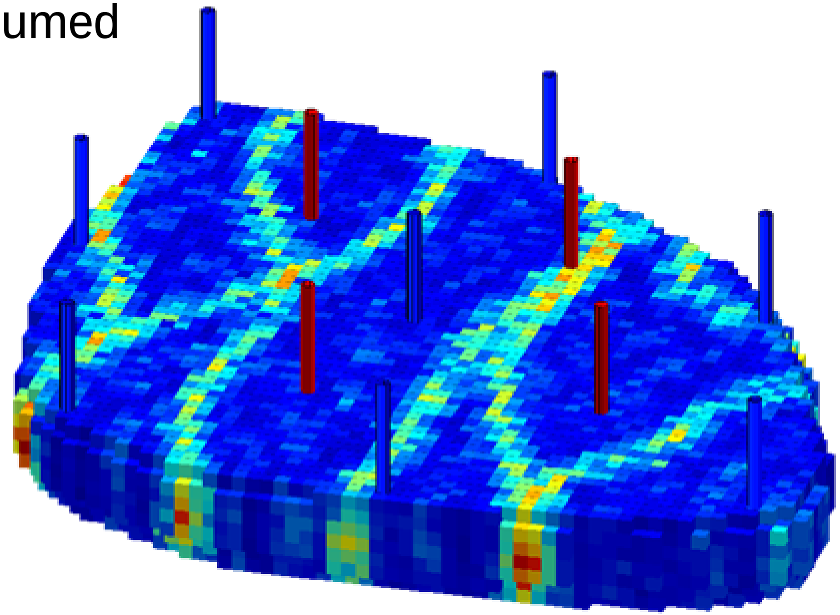
- As prior information an ensemble of initial states $\{\widehat{x}_{k|k}\}$ is generated from a given distribution
- By simulating every ensemble member, corresponding ensembles $\{\widehat{x}_{k+1|k}\}$ and $\{\widehat{y}_{k+1|k}\}$ are generated, and stored as columns of matrices $\hat{X}$ and $\widehat{Y}$ 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 $\widehat{Y}$.
- The update becomes: $\widehat{x}_{k+1|k+1} = \widehat{x}_{k+1|k} + K_{k+1}[y_{k+1} - \widehat{y}_{k+1|k}]$, where K_{k+1} is given by:

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

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

Closed-loop simulation example

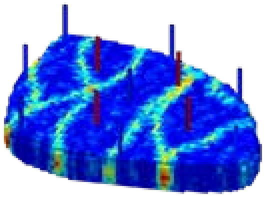
- Model with high-perm channels assumed to be ‘reality’
- Permeabilities are unknown in closed-loop control
- Period of 8 years
- Objective function: NPV
  - r_o = 10 *\$/stb*, r_w = 1 *\$/stb* and r_i = 0 *\$/stb*
  - Annual discount factor: 15%
- Measurements
  - Fractional flow rates (oil/water)
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

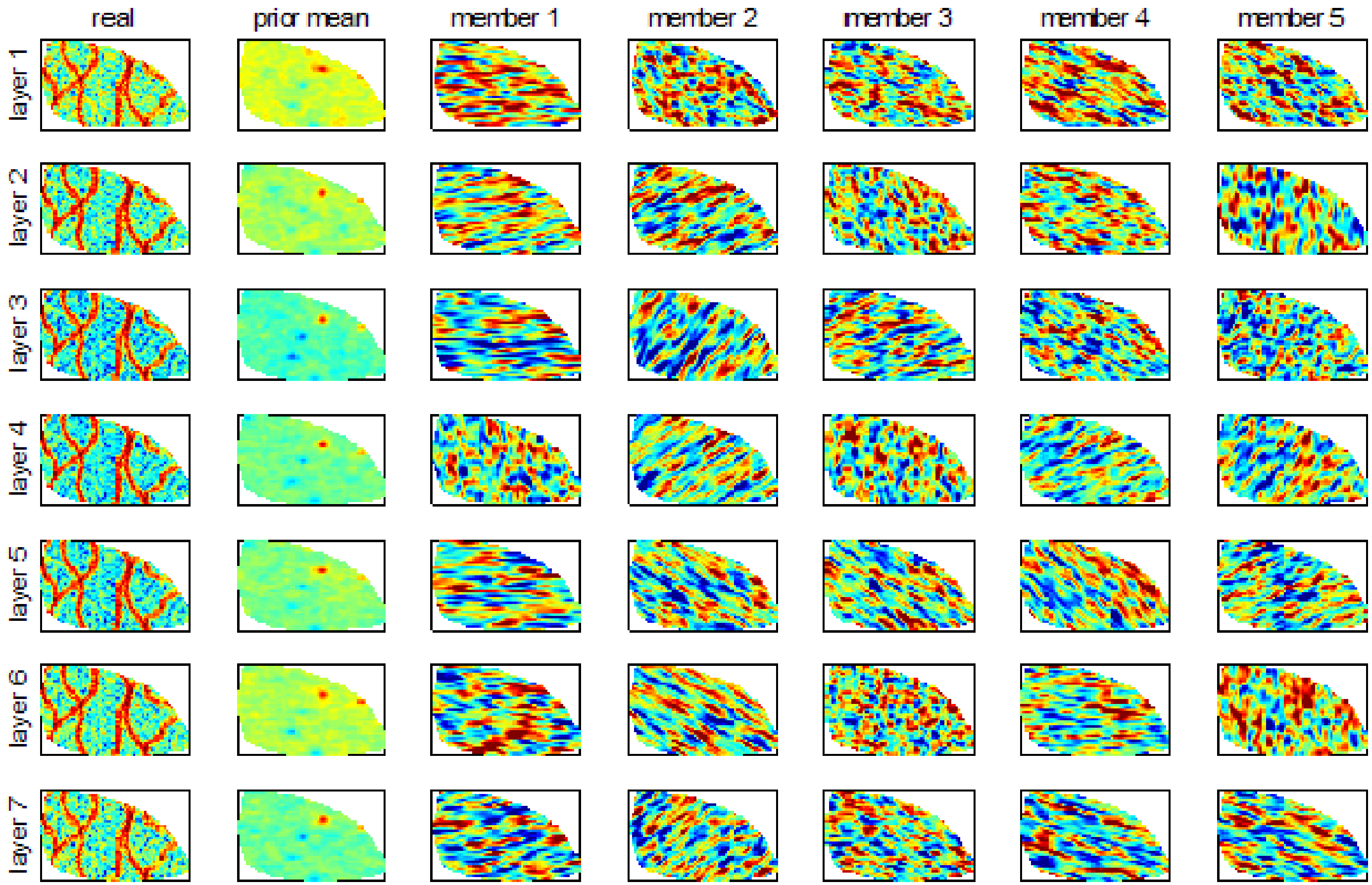


Gijs van Essen, 2006

Closed-loop simulation example

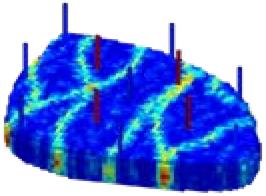
Initial ensemble

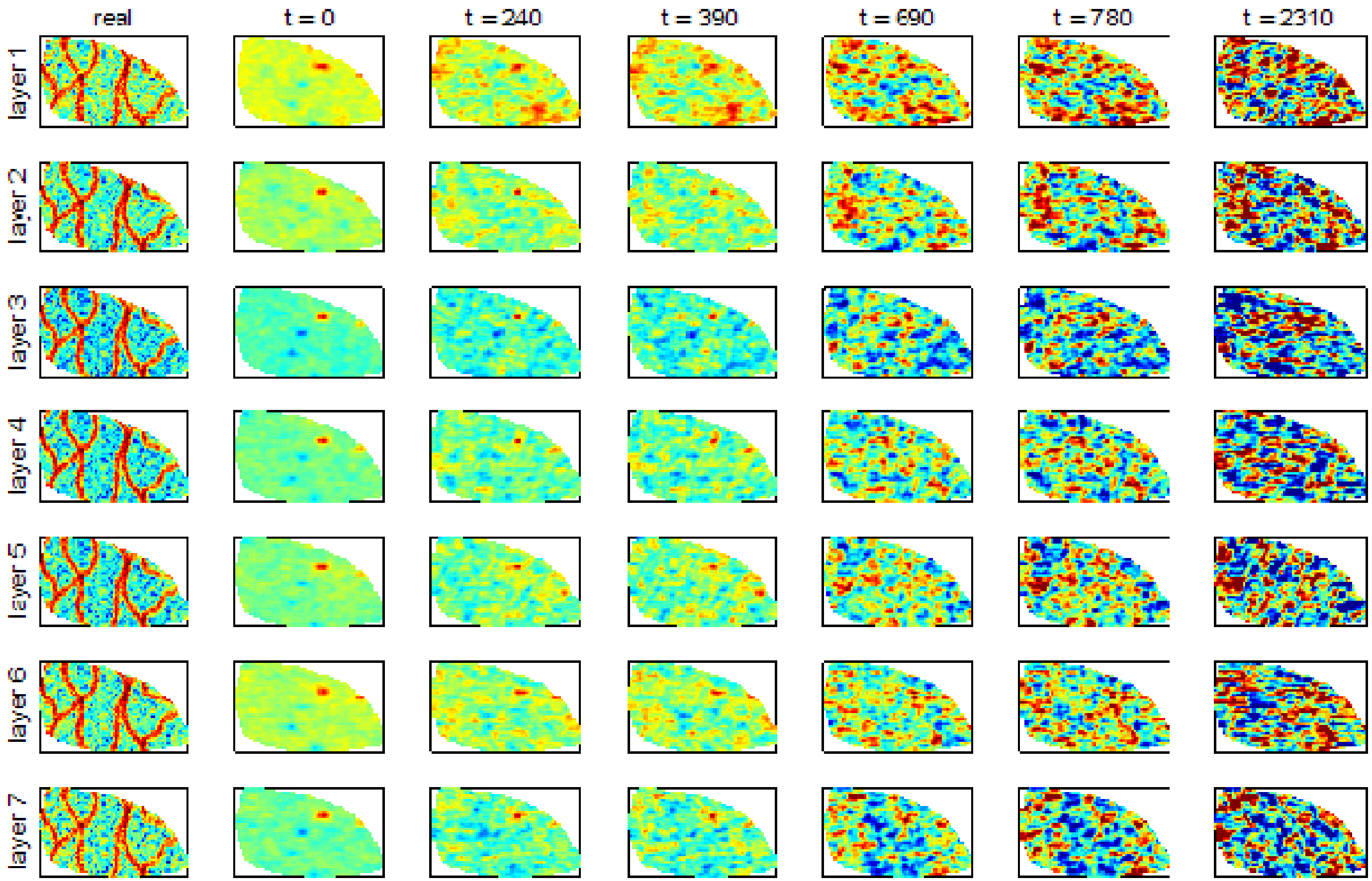




Closed-loop simulation example

Ensemble updates at different times

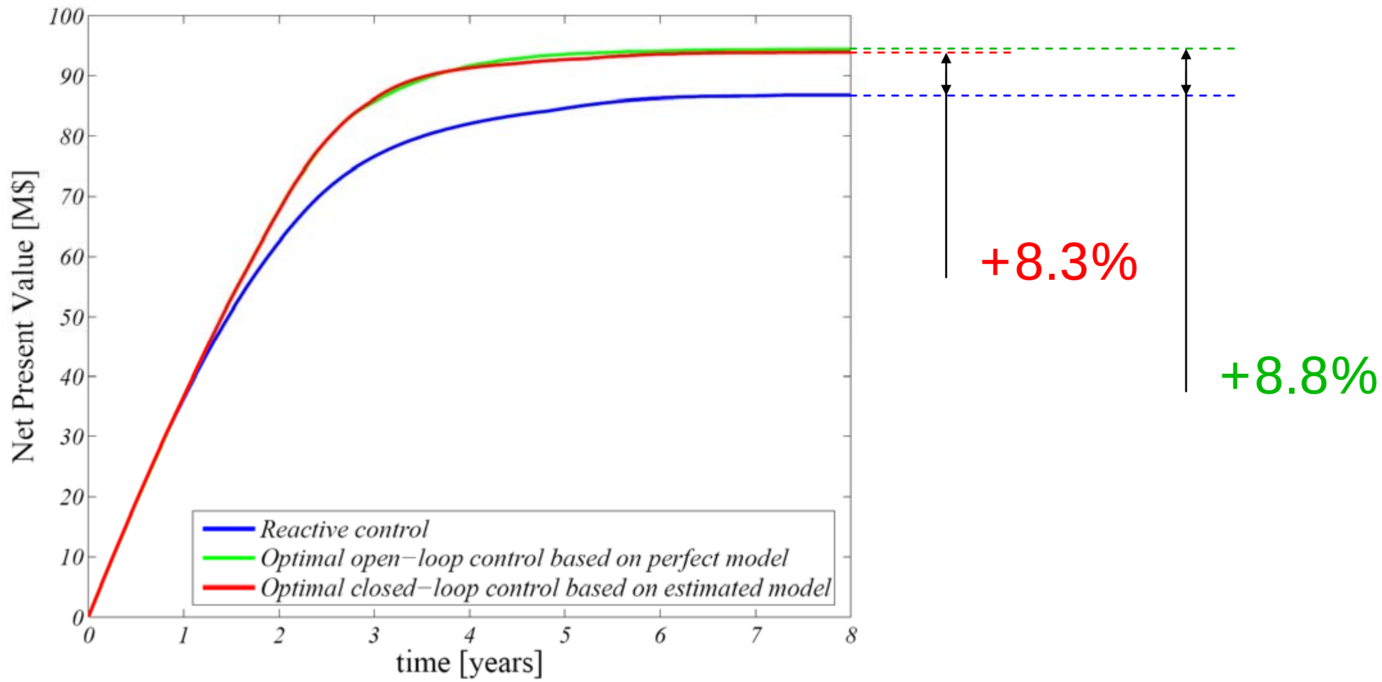




Closed-loop simulation example

Results

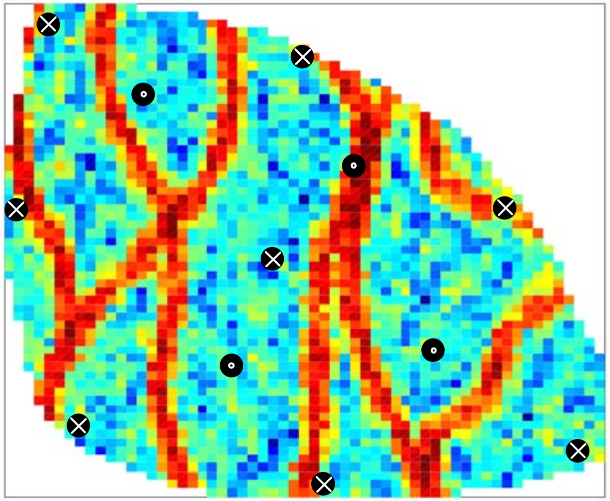
- 3 study cases: reactive control, optimal open-loop control based on perfect ('reality') model, optimal closed-loop control

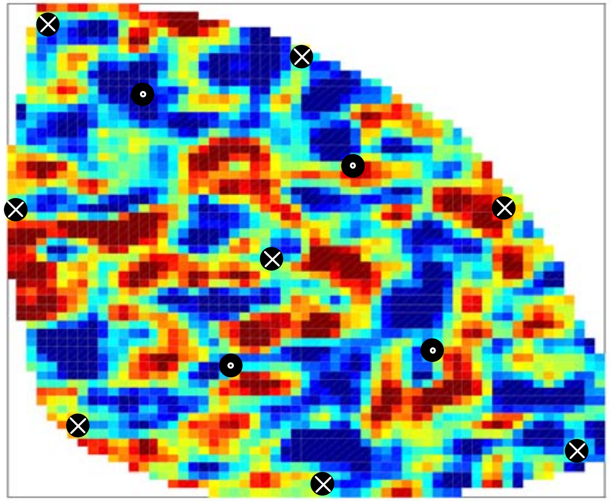


Closed-loop reservoir management

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

- 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

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

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

Limitation: only local linearized situation can be handled

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)

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?