Smart fields: model-based control and optimisation of subsurface flow

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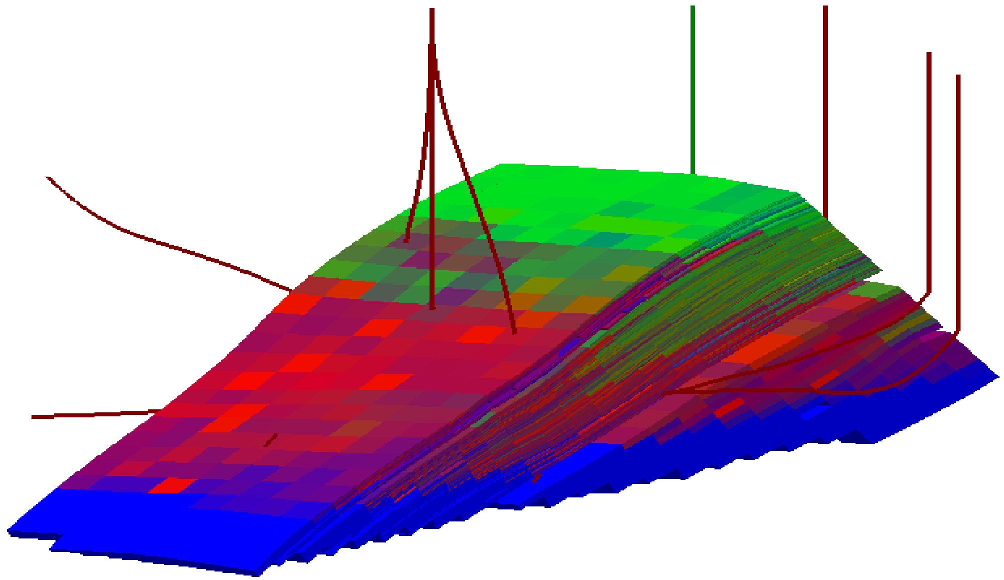


Research & development drivers

- Increasing demand; reducing supply
  - energy demand continues to grow world-wide
  - renewables are developing too slow to keep up with demand
  - ‘easy oil’ has been found; few new discoveries; complex fields

=> produce more from existing reservoirs

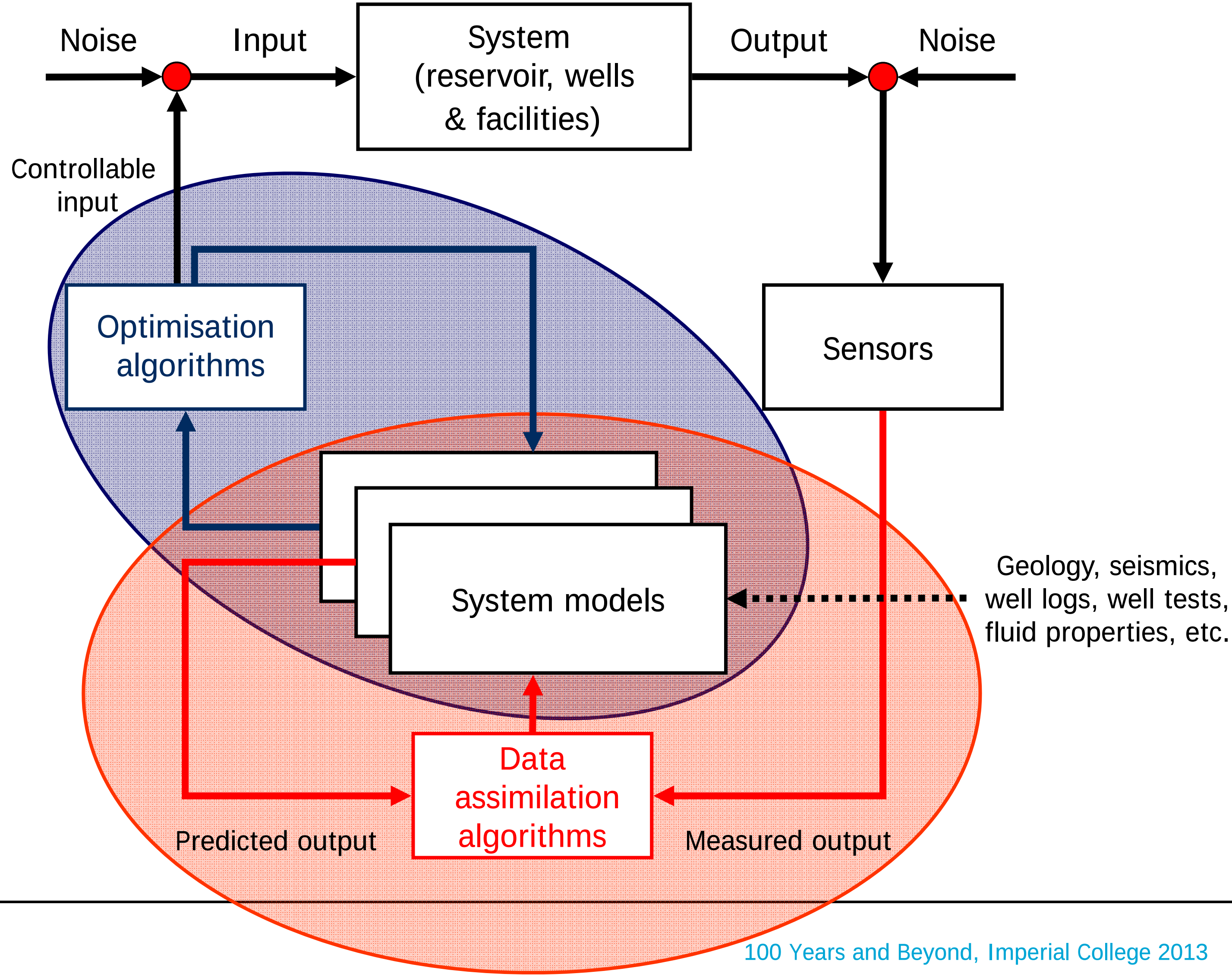
- Increasing knowledge- and data intensity
  - more sensors: pressure/temperature/flow, time-lapse seismics, passive seismics, EM, tilt meters, remote sensing, ...
  - more control: multi-lateral wells, smart wells, snake wells, dragon wells, remotely controlled chokes, ...
  - more modeling capacity: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

=> use a model-based systems and control approach

Closed-loop reservoir management

- Hypothesis: recovery can be significantly increased by changing reservoir management from a ‘batch-type’ to a near-continuous model-based controlled activity
- Key elements:
  - Optimisation under geological uncertainties
  - Data assimilation for frequent updating of system models
- Inspiration:
  - Systems and control theory
  - Meteorology and oceanography
- A.k.a. real-time reservoir management, quantitative reservoir management, computer-assisted reservoir management, smart fields, intelligent fields, ...

Closed-loop reservoir management



CLRM perspectives

Geoscience-focused

- Maximize subsurface knowledge
- Relevant for field development planning
- Geological model(s) at the core

Production-focused

- Maximize financial outcome
- Relevant for surveillance and intervention
- Flow model(s) at the core

CLRM perspectives

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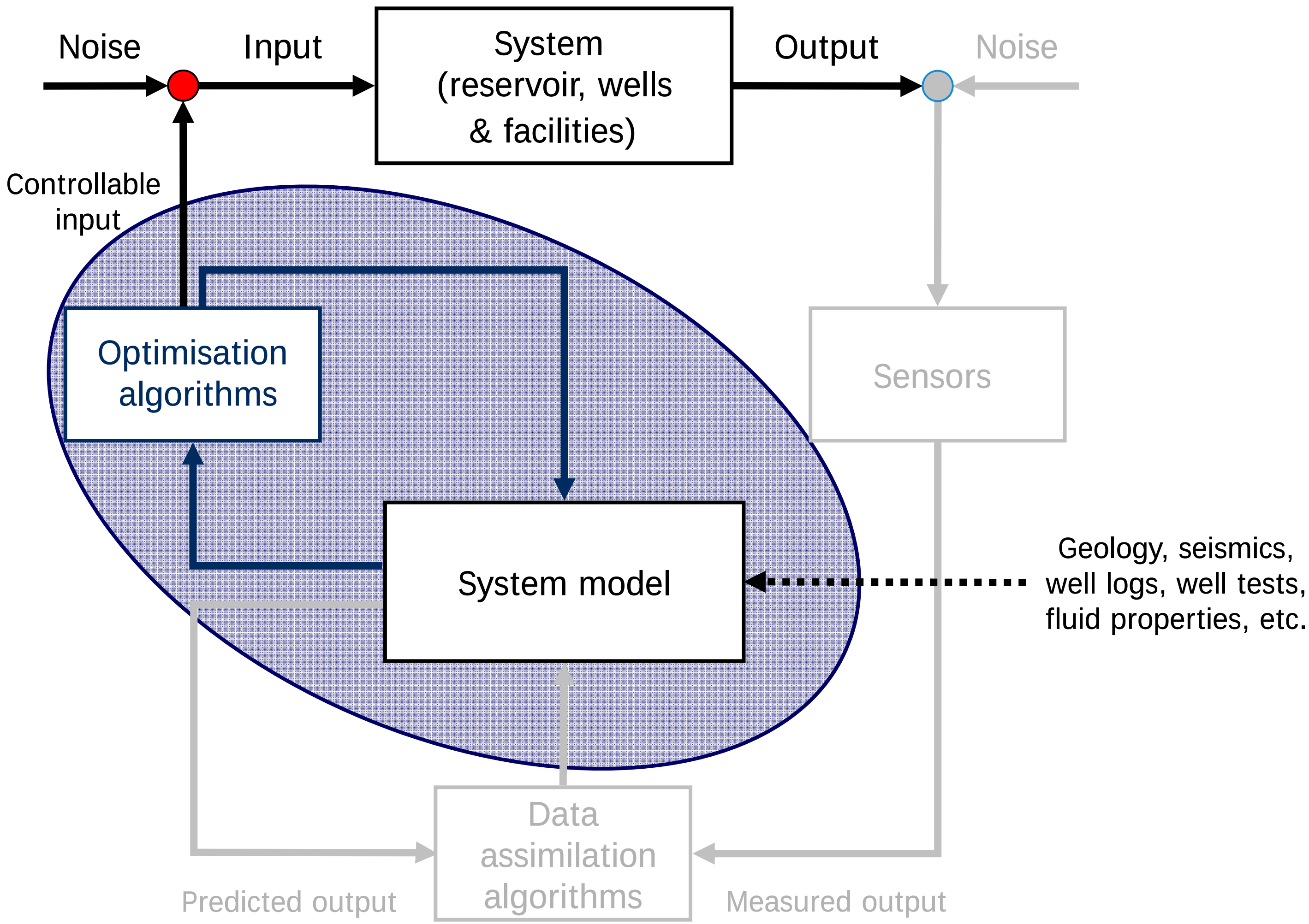
Open-loop flooding optimisation



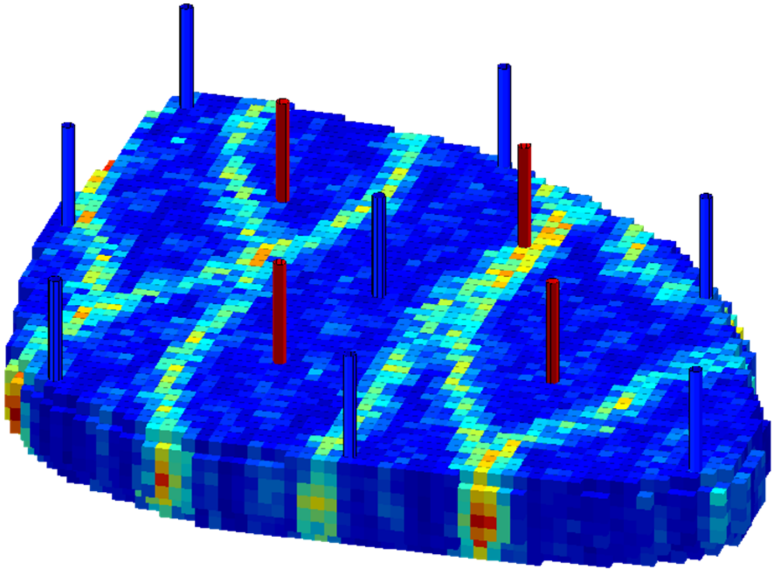
Optimisation techniques

- Global versus local
- Gradient-based versus gradient-free
- Constrained versus non-constrained
- ‘Classical’ versus ‘non-classical’ (genetic algorithms, simulated annealing, particle swarms, etc.)
- We use ‘adjoint-based optimal control theory’
  - Gradient-based – local optimum
  - Computational effort independent of number of controls
  - Objective function: ultimate recovery or monetary value
  - Controls: injection/production rates, pressures or valve openings
  - Beautiful, but code-intrusive and requires lots of programming

Anyway, the magic isn’t in the method

12-well example

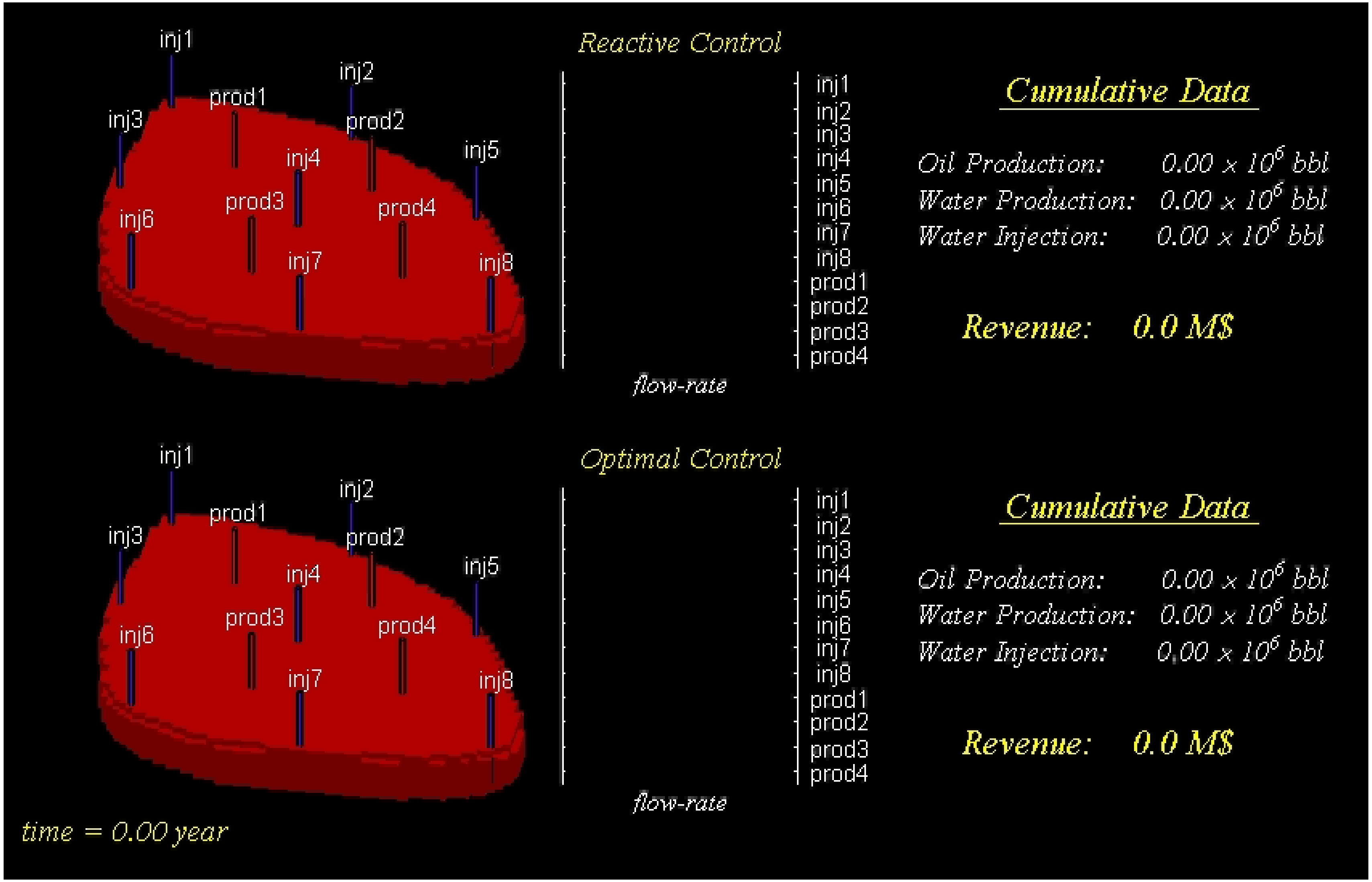
- 3D reservoir
- High-permeability channels
- 8 injectors, rate-controlled
- 4 producers, BHP-controlled
- Production period of 10 years
- 12 wells x 10 x 12 time steps
  gives 1440 optimization parameters
- Optimisation of monetary value J



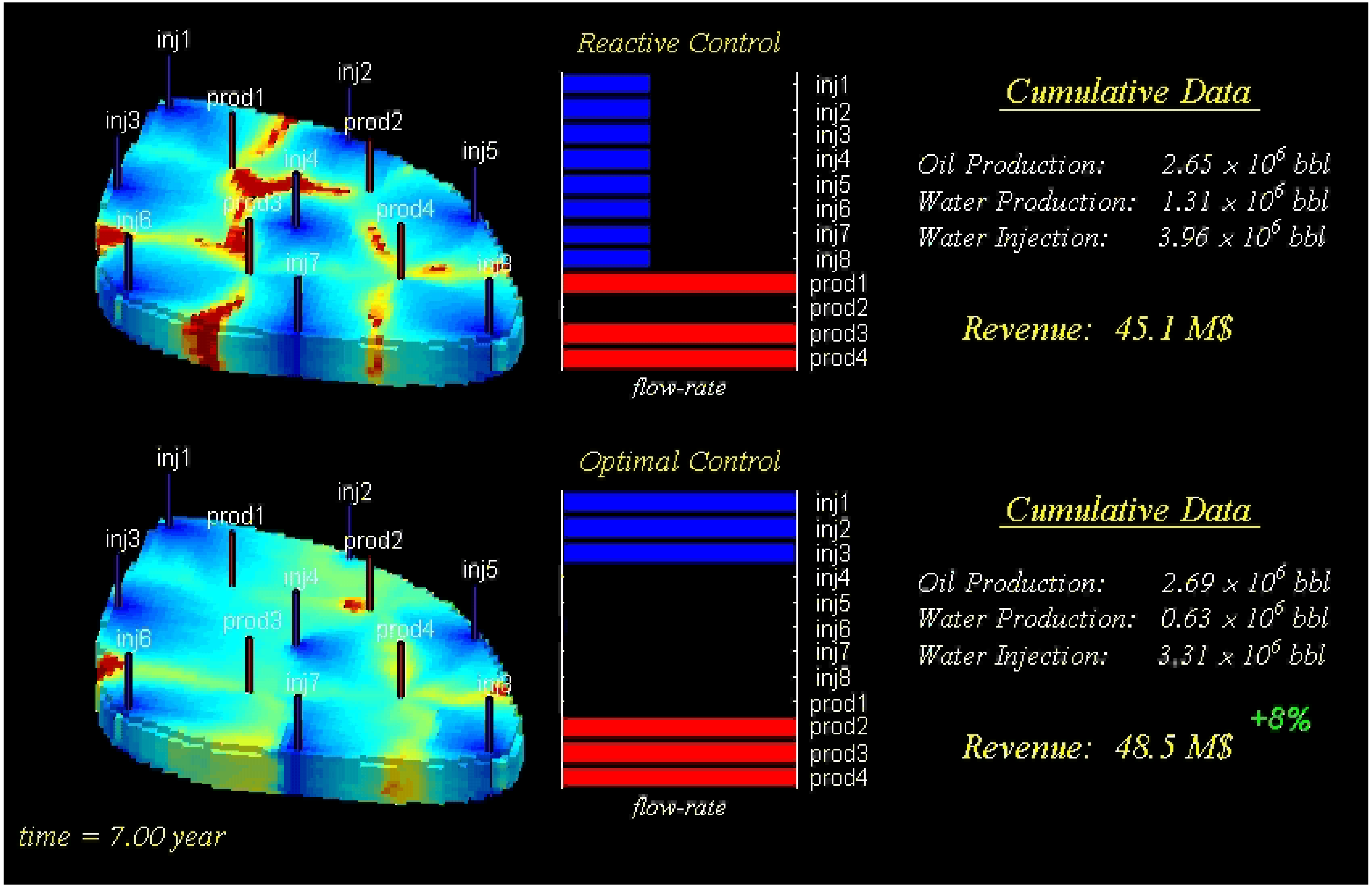
Van Essen et al., 2006

J = (value of oil – costs of water produced/injected)

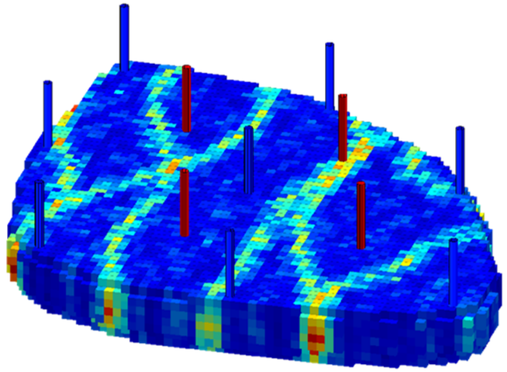
12-well example



12-well example

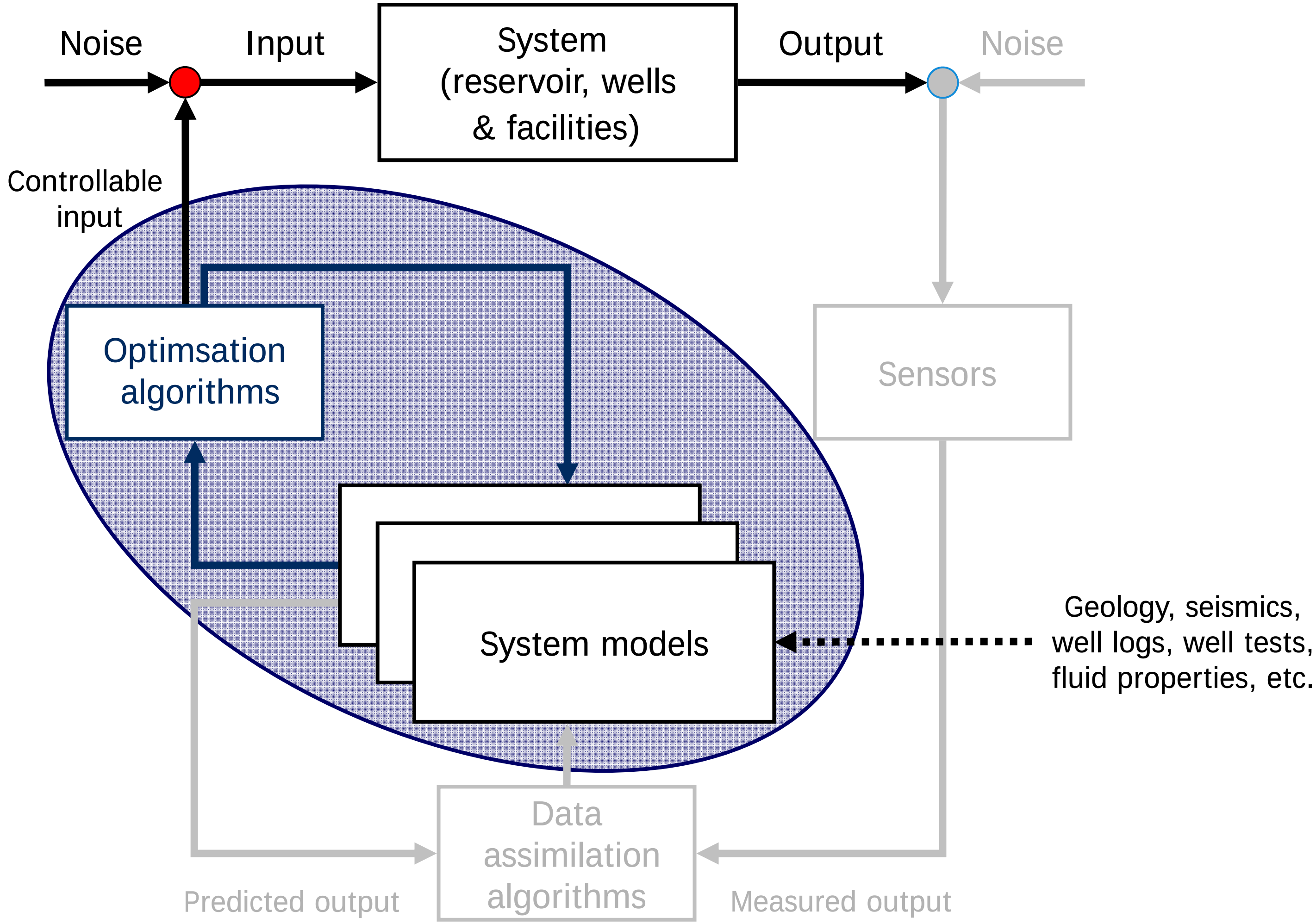


Why this wouldn't work



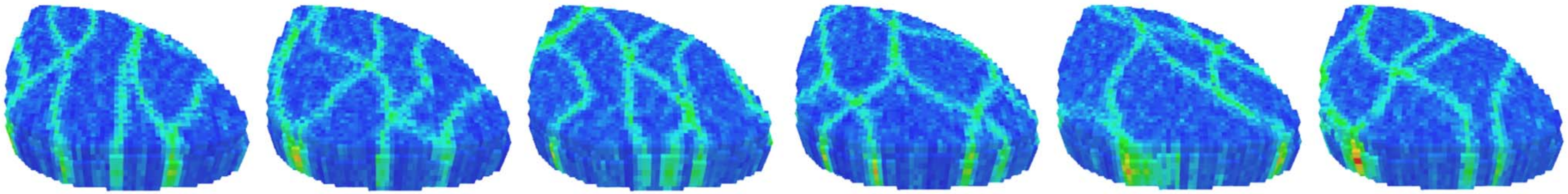
- Real wells are sparse and far apart
- Real wells have more complicated constraints
- Field management is usually production-focused
- Long-term optimisation may jeopardize short-term profit
- Optimal inputs cannot be implemented (too dynamic)
- Production engineers don't trust reservoir models anyway
- We do not know the reservoir!

Robust optimisation



Robust optimization

- Use ensemble of realizations (typically 100)

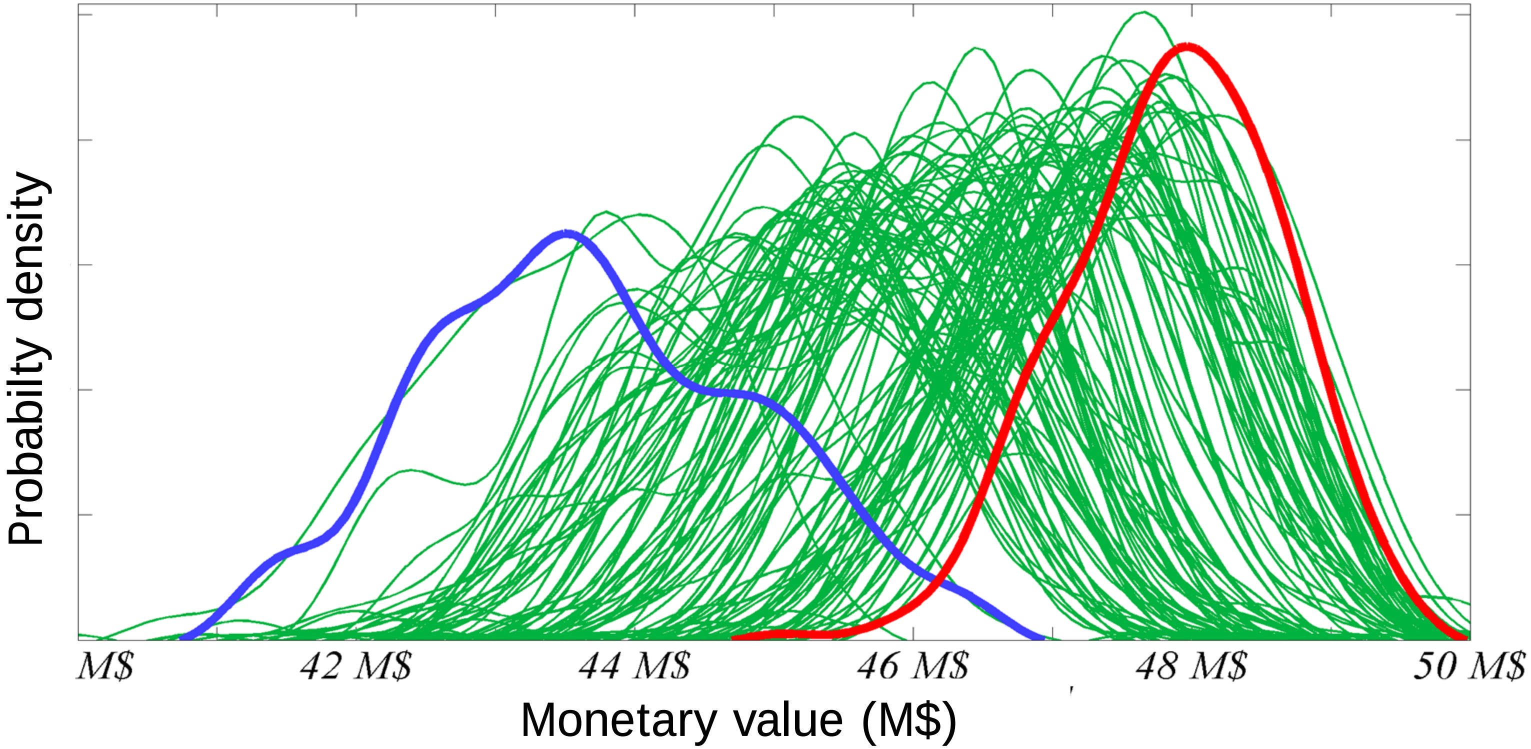


Van Essen et al., 2006

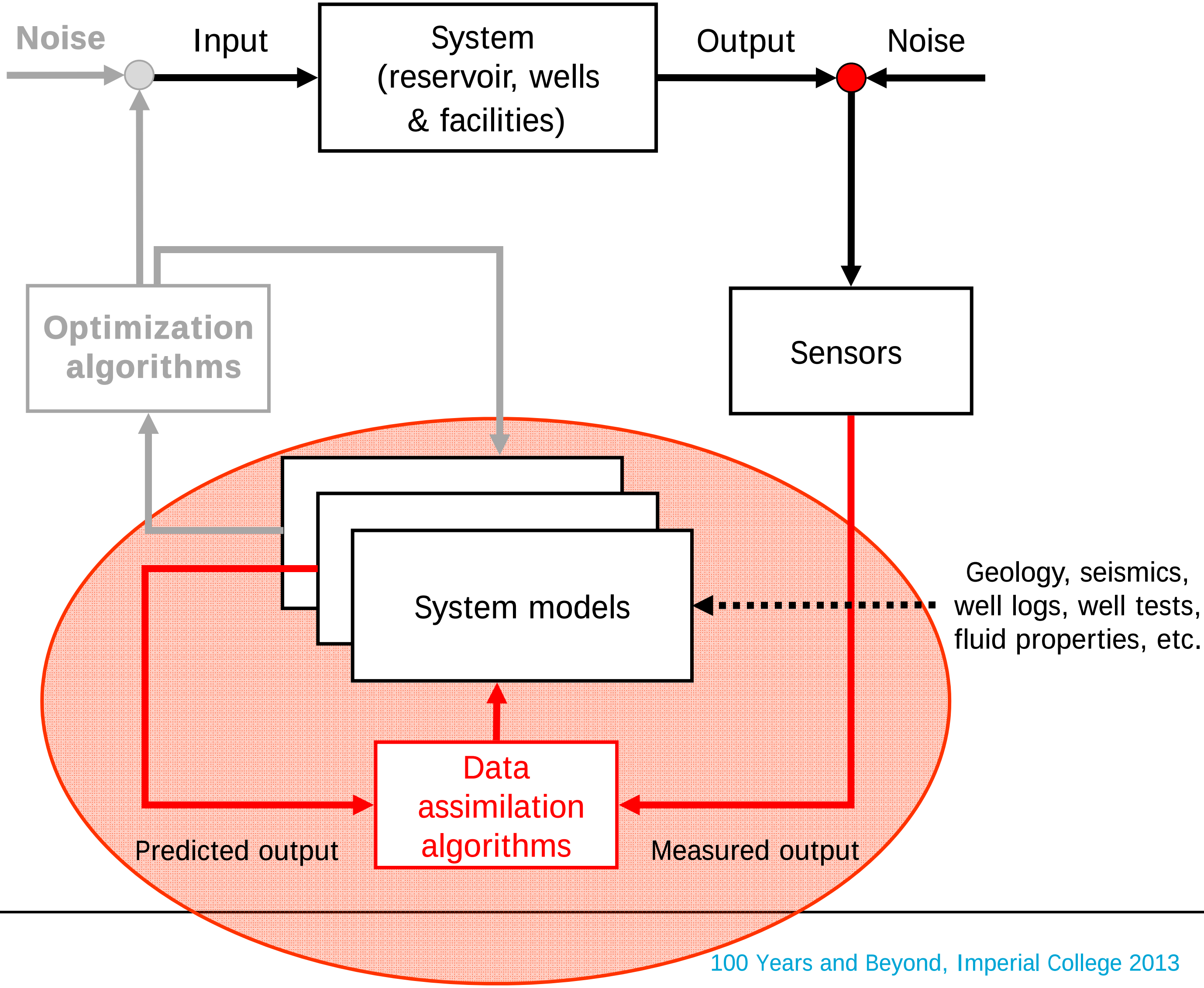
- Optimize expected value over ensemble
- Single strategy, not 100!
- If necessary include risk aversion (utility function)
- Computationally intensive

Robust optimisation results

3 control strategies applied to set of 100 realisations:
reactive control, nominal optimisation, robust optimisation



Computer-assisted history matching

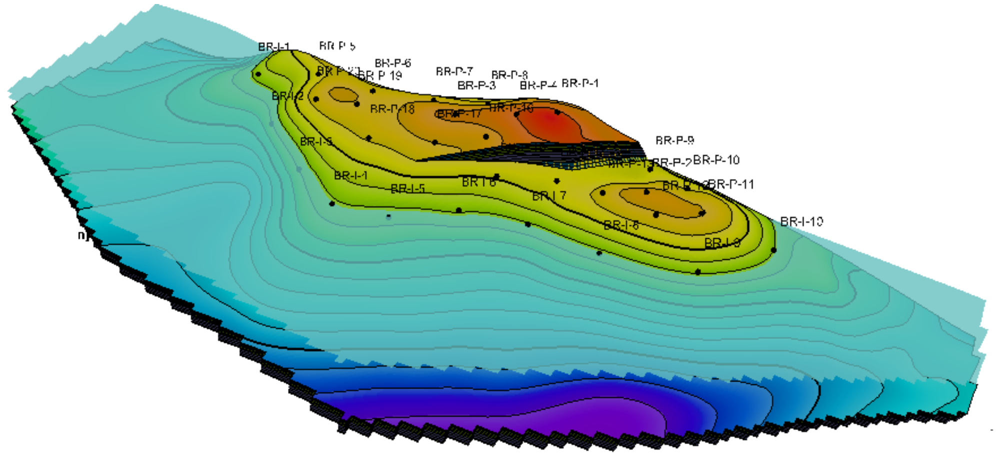


Computer-assisted history matching (data assimilation)

- Uncertain parameters: permeabilities, porosities, fluid properties, aquifers, fault positions, horizon depths ...
- Data: production (oil, water, pressure), 4D seismics, ...
- Very ill-posed problem: many parameters, little info
- Variational methods – Bayesian framework:
- Ensemble Kalman filtering – sequential methods
- Reservoir-specific methods (e.g. streamlines)
- 'Non-classical' methods – simulated annealing, GAs, ...
- Monte Carlo methods – MCMC with proxies

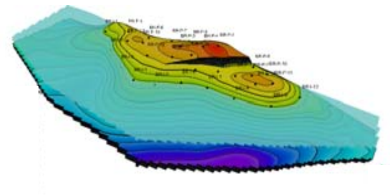
Also here, the magic isn't in the method

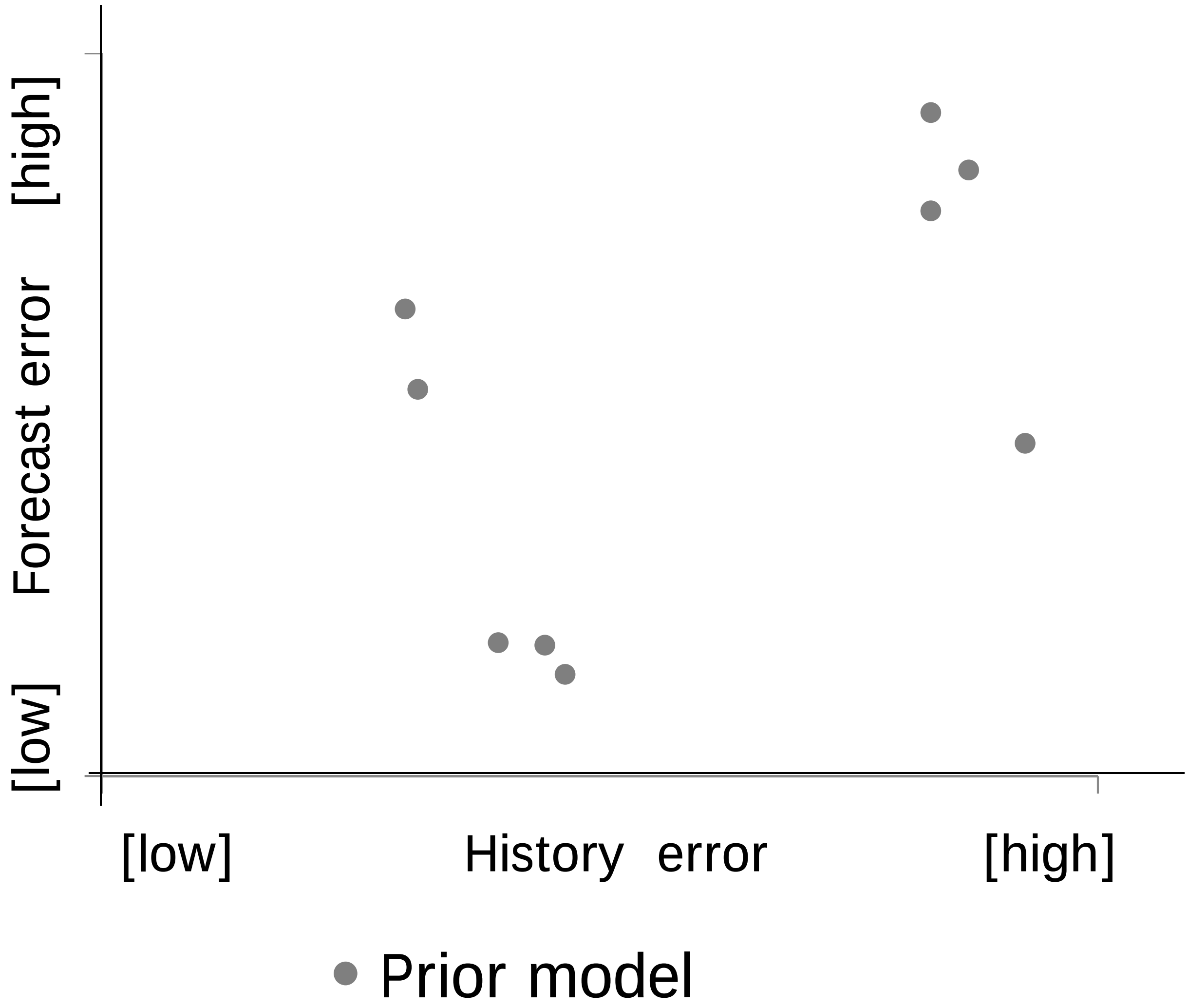
Example, Brugge field



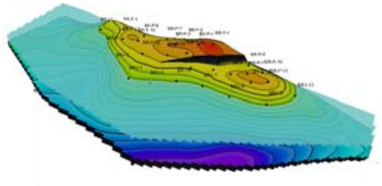
- Brugge field
  (SPE workshop on CLRM)
- 10 water injectors
- 20 smart producers
- Production data until 10 yrs
- '4D seismics' after 5 and 10 years
- 104 prior models (we used 9)
- Optimisation over remaining 20 years
- Question: effect of adding 4D seismics on production forecast?
- Measures: root-mean squared difference between historic (10 yrs) and future (20 yrs) production data (oil, water rates)

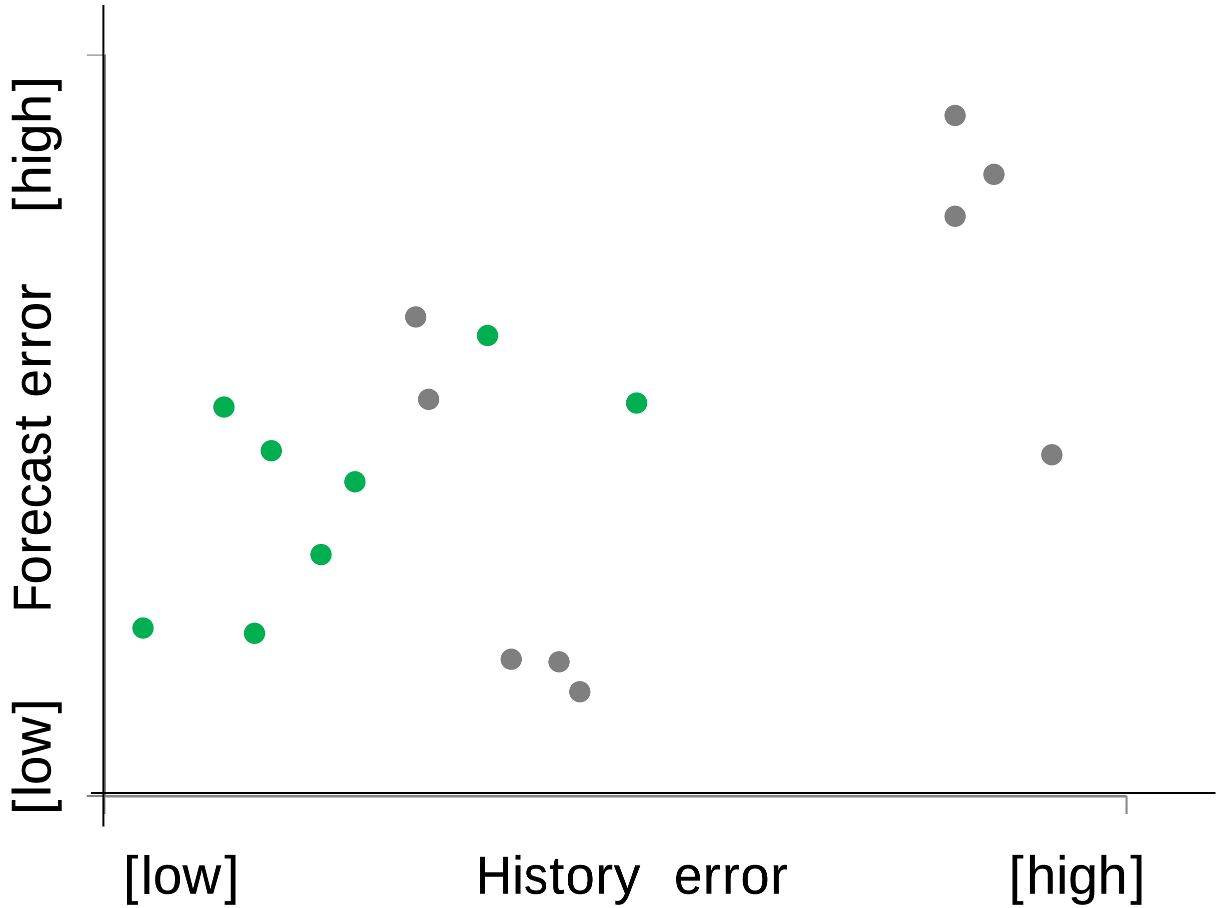
Effect of adding 4D seismics (1)





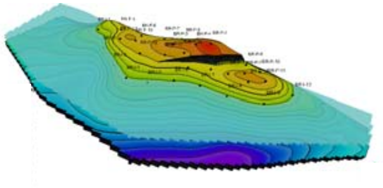
Effect of adding 4D seismics (2)

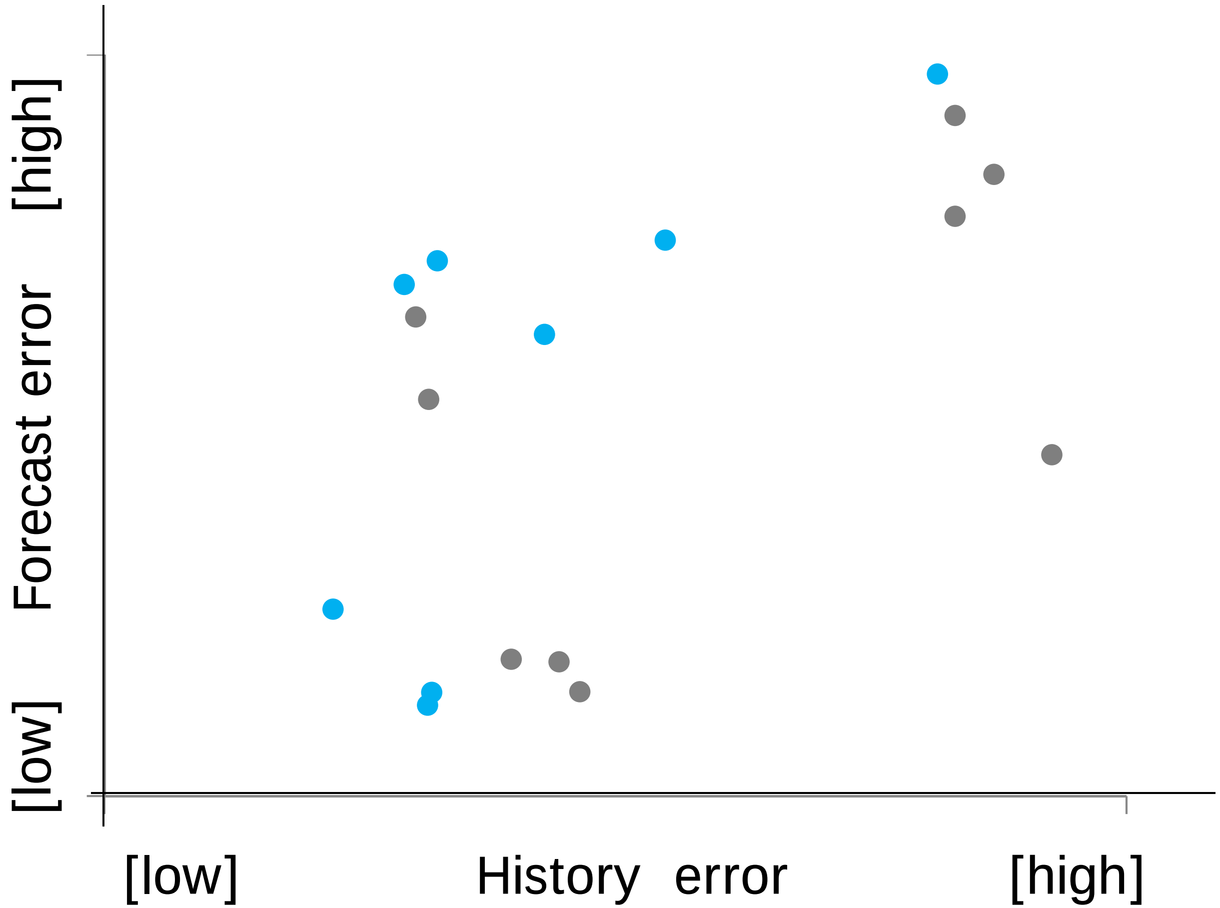




- After assimilating production data

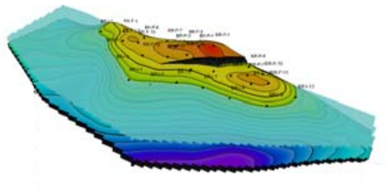
Effect of adding 4D seismics (3)

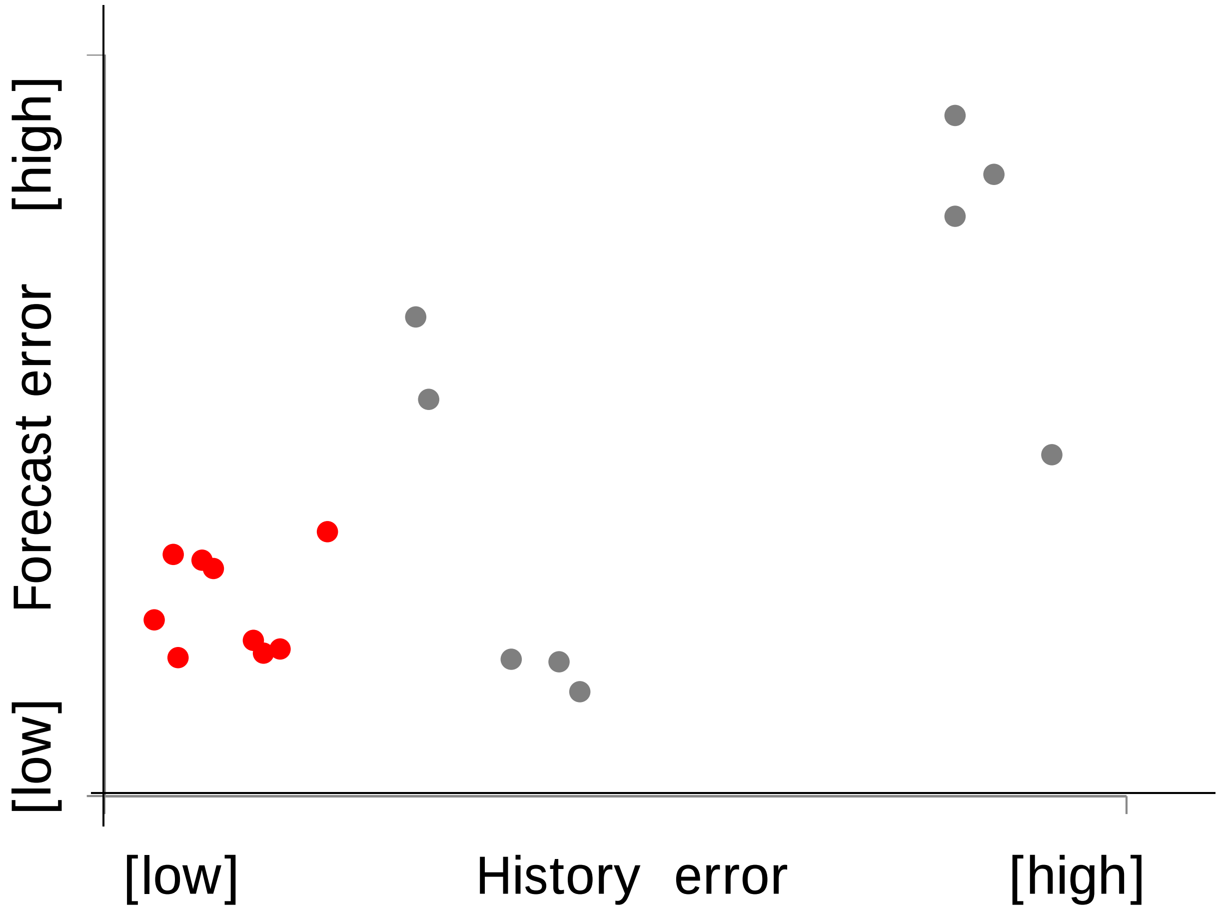




• After assimilating 4D seismic data

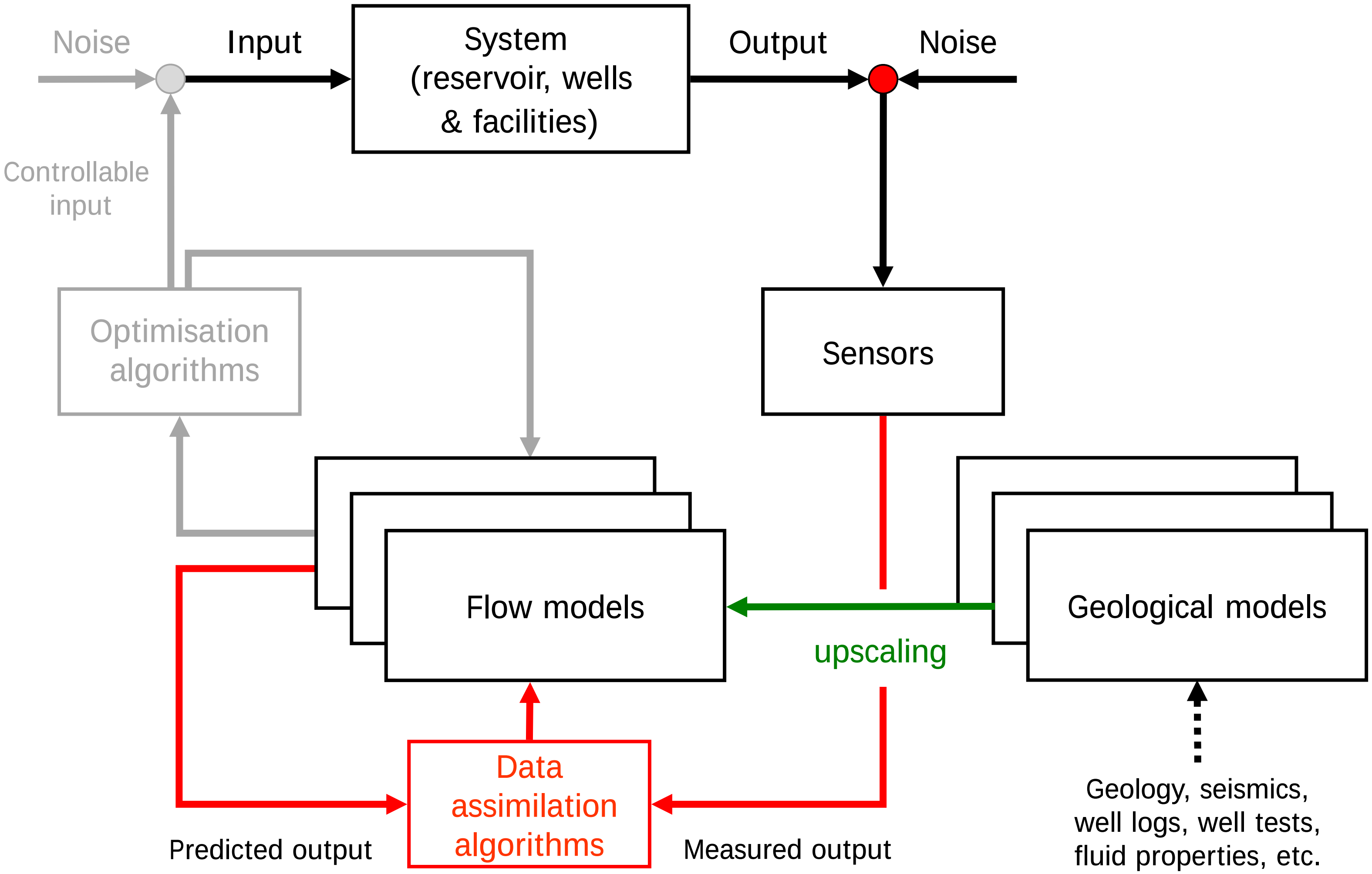
Effect of adding 4D seismics (4)



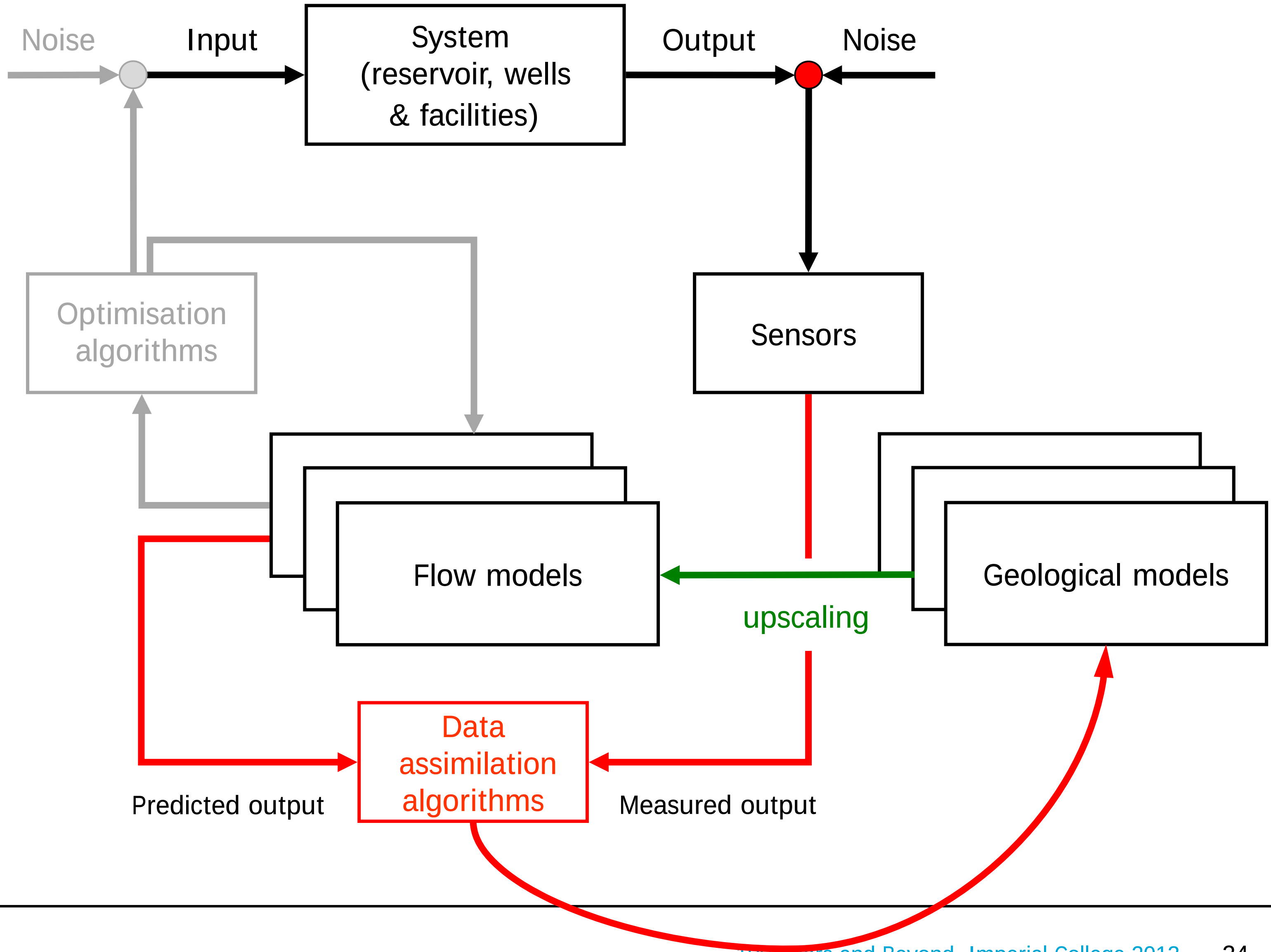


- After assimilating production and 4D seismic data

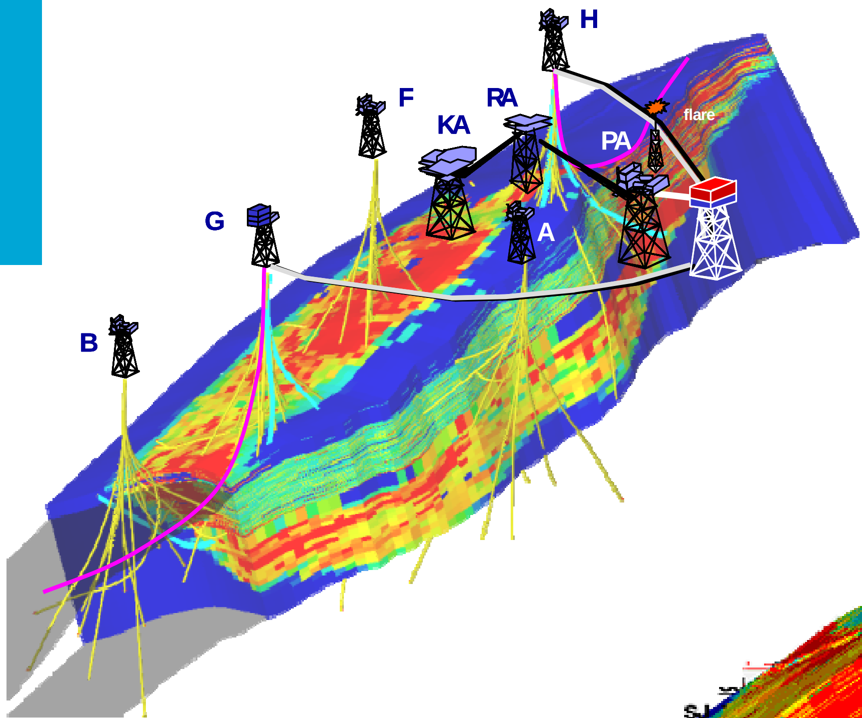
Conventional history matching



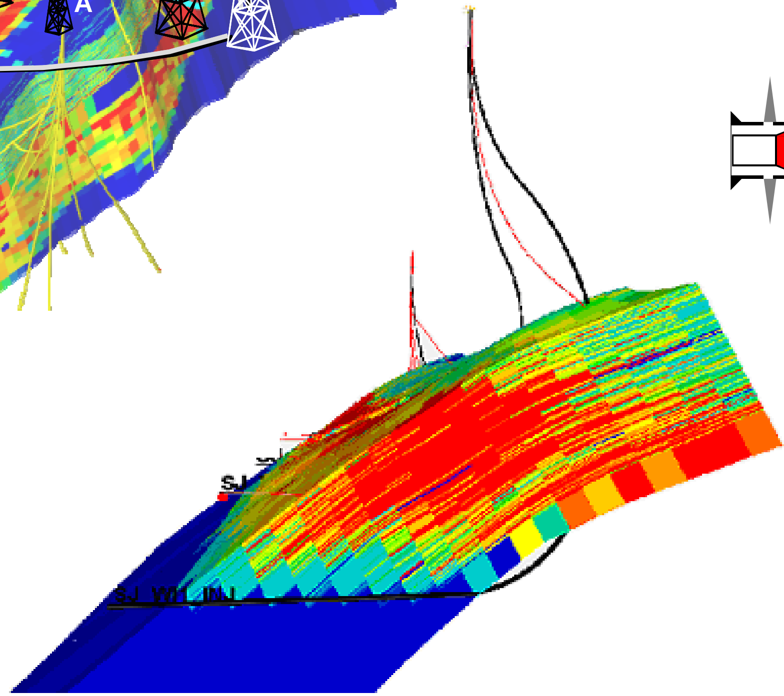
Big-loop history matching (2)

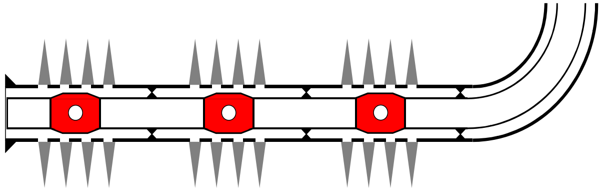


Optimization of ‘smart’ horizontal wells



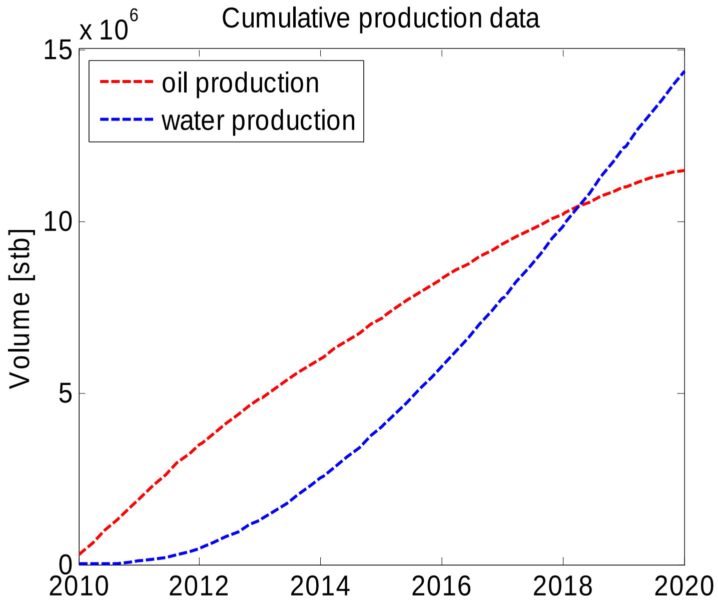
Answer (joint TU Delft – Shell research): Combine-large scale reservoir simulation with adjoint-based optimisation.

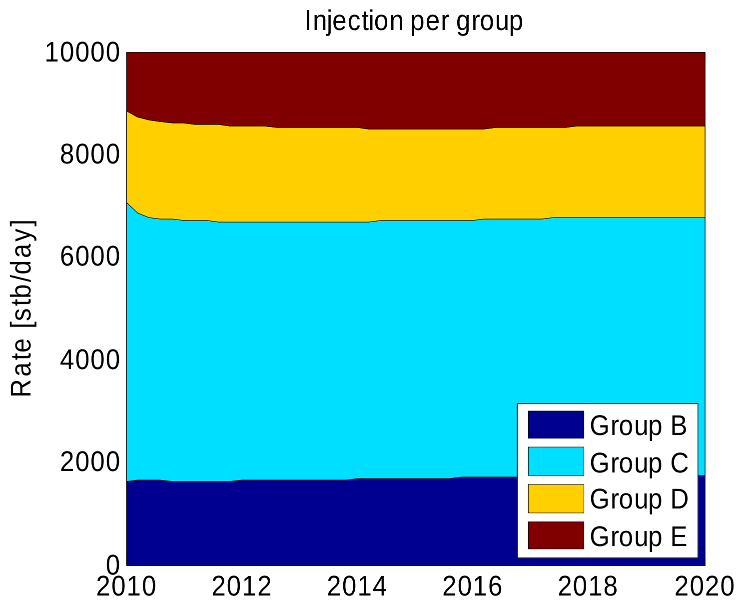




Question from Shell: How to optimise the valve settings over time for a ‘smart’ horizontal water injection well?

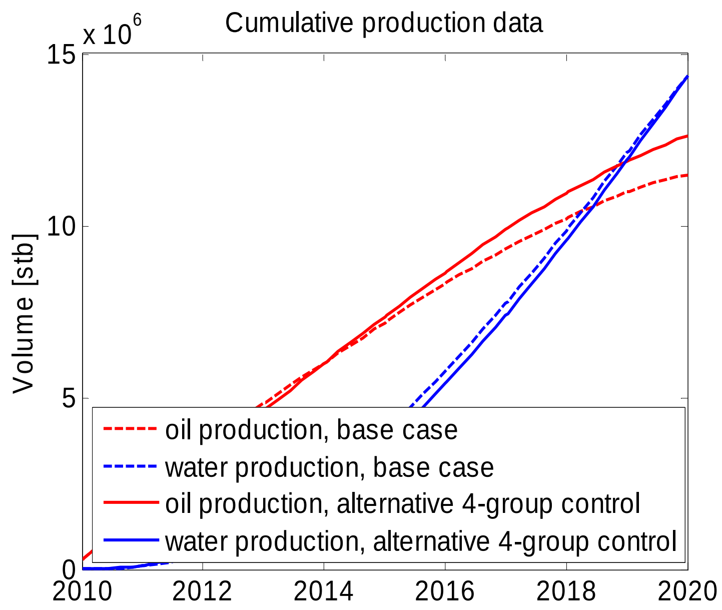
Base case results

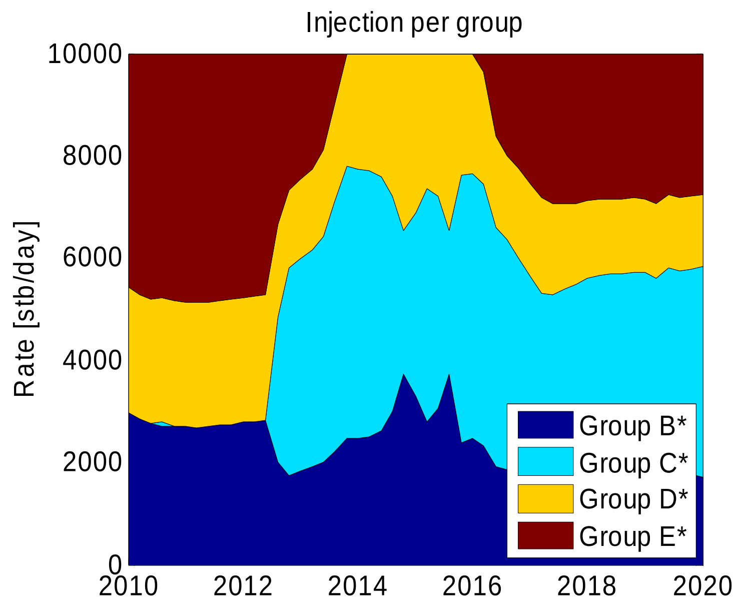




- Grouping based on geological features
- Cumulative oil production: 11,47 MMstb

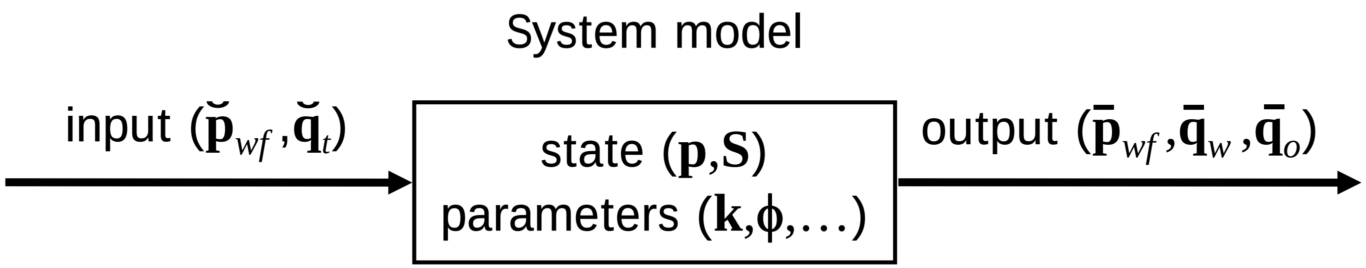
Alternative 4-group control





- Cumulative oil production: 12,62 MMstb
- Increase of 10,0% (1,15 MMstb)

System-theoretical concepts



- Controllability of a dynamic system is the ability to influence the states through manipulation of the inputs.
- Observability of a dynamic system is the ability to determine the states through observation of the outputs.
- Identifiability of a dynamic system is the ability to determine the parameters from the input-output behavior.
- Well-defined theory for linear systems. More difficult for nonlinear ones.

System theory – main findings so far

- Controllability, observability and identifiability are very limited
- Reservoir dynamics ‘lives’ in a state space of a much smaller dimension than the number of model grid blocks
- Linear case (pressures only): typical number of relevant pressure states: 2 x # of wells
- For fixed wells: the (few) identifiable parameter patterns correspond just to the (few) controllable state patterns
- Scope for reduced-order modeling to speed up iterative optimisation, history matching, upscaling?
  - First attempts: POD – disappointing speed-ups
  - Successful: TPWL (Durlofsky et al.)
  - Other approaches: DEIM, sparse representations, ... in progress

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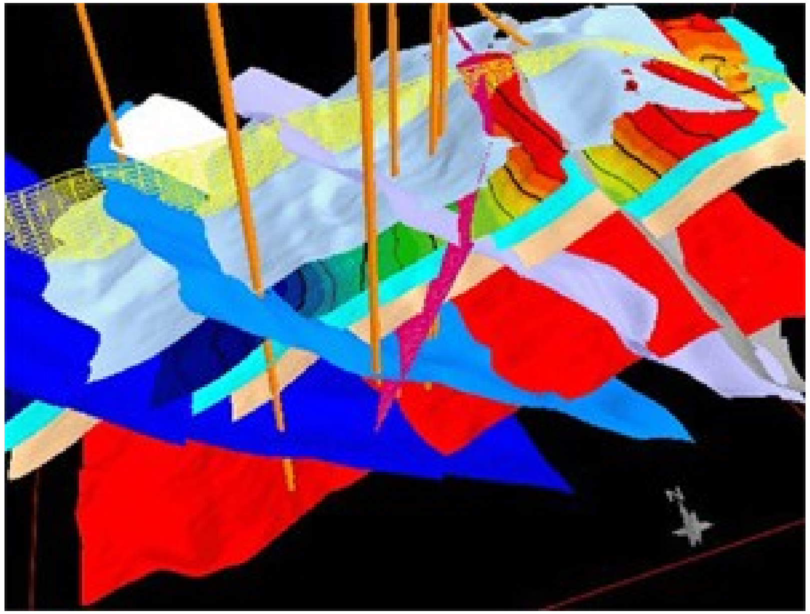
So, do we still need geology?

System theory – main findings so far

Yes, we very much need geology!



System theory – main findings so far

Yes, we very much need geology!

- Interpreting the 'history matched' results requires geological insight
- Understanding optimisation results also requires geological insight
- Well location-optimisation requires a geological model
- However, we need to focus on the relevant geology:
    - Which geological features are identifiable?
    - Which geological features influence controllability?

Conclusions, questions, more work

- Specific optimisation methods less important than workflow & human interpretation of results
- Use of multiple models to capture uncertainties is essential
- Reservoir dynamics lives in low-order space – so what?
- Control-relevant geology – how do we define it?
- Developments: well location/trajectory optimisation, infill drilling scheduling, EOR optimisation, big loop, model maturation, structural uncertainties, multiple data sources (4-D seismics, gravity, EM, passive seismics, ...)

Acknowledgments

- Collaborators:

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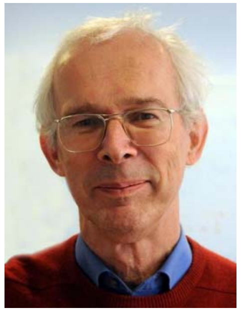
  Arnold Heemink

  Paul Van den Hof



and many other colleagues and students of

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- TU Delft – Delft Center for Systems and Control
- TU Delft – Delft Institute for Applied Mathematics
- TU Eindhoven – Department of Electrical Engineering
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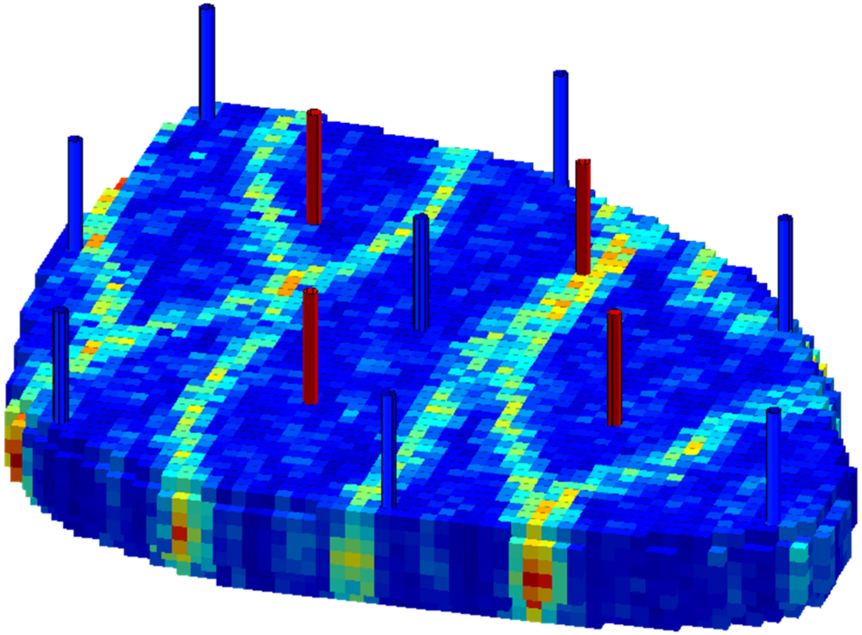
Questions?



www.citg.tudelft.nl/smart