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

System (reservoir, wells & facilities)

Noise
Input

Controllable input

Optimisation algorithms

System models

Data assimilation algorithms

Predicted output

Measured output

Sensors

Geology, seisms, well logs, well tests, fluid properties, etc.
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

Noise → Input

Controllable input → Optimisation algorithms

System (reservoir, wells & facilities)

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System model

Predicted output → Measured output

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Input

Noise

Output
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 $J$

$$J = (\text{value of oil} - \text{costs of water produced/injected})$$
12-well example

**Cumulative Data**

- **Oil Production:** $0.00 \times 10^6$ bbl
- **Water Production:** $0.00 \times 10^6$ bbl
- **Water Injection:** $0.00 \times 10^6$ bbl

**Revenue:** $0.0 M\$$

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**Reactive Control**

- **Cumulative Data**
- **Revenue:** $0.0 M\$

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**Optimal Control**

- **Cumulative Data**
- **Revenue:** $0.0 M\$

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*time = 0.00 year*
12-well example

Cumulative Data

Oil Production: \(2.65 \times 10^6\) bbl
Water Production: \(1.31 \times 10^6\) bbl
Water Injection: \(3.96 \times 10^6\) bbl

Revenue: \(45.1\ M\$\)

Cumulative Data

Oil Production: \(2.69 \times 10^6\) bbl
Water Production: \(0.63 \times 10^6\) bbl
Water Injection: \(3.31 \times 10^6\) bbl

Revenue: \(48.5\ M\$\) \(+8\%\)
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

- Noise
- Input
- System (reservoir, wells & facilities)
- Output
- Noise

Optimisation algorithms

System models

Data assimilation algorithms

Geology, seismics, well logs, well tests, fluid properties, etc.

Controllable input

Predicted output

Measured output

Sensors
Robust optimization

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

Van Essen et al., 2006
Robust optimisation results

3 control strategies applied to set of 100 realisations: reactive control, nominal optimisation, robust optimisation
Computer-assisted history matching

**Diagram:**
- **Input** feeding into the **System** (reservoir, wells & facilities).
- **Noise** affecting the system.
- **Sensors** collecting data feeds into **System models**.
- **Data assimilation algorithms** adjust the system models.
- **Predicted output** from the models compared to **measured output**.
- **Optimization algorithms** further refine the system models.

**Data Sources:**
Geology, seismics, well logs, well tests, fluid properties, etc.
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 seisms’ after 5 and 10 years
- 104 prior models (we used 9)
- Optimisation over remaining 20 years
- Question: effect of adding 4D seisms 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)

- Forecast error
- History error
- Prior model
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

System (reservoir, wells & facilities)

Flow models

Predicted output

Data assimilation algorithms

Geological models

Geology, seismics, well logs, well tests, fluid properties, etc.

Measured output

Optimisation algorithms

Sensors

Upscaling

Input

Output

Noise

Connectable input

Noise Output

Input (reservoir, wells & facilities)
Big-loop history matching (2)

[Diagram showing the flow of data assimilation algorithms through system, sensors, flow models, geological models, and predicted/measured output, with noise and upscaling.]
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: $2 \times \# \text{ of wells}$
- 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, …)
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Questions?

www.citg.tudelft.nl/smart