Closed-loop reservoir management
- A control perspective

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Outline
1. Closed-loop control – performance limitations
2. Closed-loop vs. Open-loop control
3. Model Predictive Control (MPC) – a game changer in the downstream industries
4. Model complexity – lessons from control
5. Closed-loop reservoir management – challenging the present structure
6. Process control hierarchy – a well functioning structure in the process industries
Closed-loop control – basic properties

Control inputs
- Wellbore pressures in producers
- Injection rates

Output data
- Production rates; and oil/water, gas/oil ratios
- Seismic surveys

Assumptions
- Can influence the system through some input variables
- Can observe the system through some output variables
- Outputs can be coupled to some important performance measure

Closed-loop control depends on causality (cause – effect in time) between control inputs and system outputs

How does this relate to reservoir management and petroleum production?

Control inputs
- Wellbore pressures in producers
- Injection rates

Output data
- Production rates; and oil/water, gas/oil ratios
- Seismic surveys

Why closed-loop control
- Dampen the effect of disturbances and/or uncertainties
- Follow a reference trajectory
- Stabilize unstable systems
Closed-loop control – performance limits

Goal: Keep Output=1

Disturbance/uncertainty

Control inputs → System → Output data

Control inputs

System

Output data

Step response 2nd order system

Step response 2nd order system with disturbance
Closed-loop control – performance limits

Goal: Keep Output=1

Disturbance/uncertainty

Control inputs → System → Output data

Reference trajectory

Control law → Control inputs → System → Output data
Closed-loop control – performance limits

- Increase loop time-delay by 100
- Unchanged control strategy
- Close-to-unstable response
- Controller de-tuning is required

Goal: Keep Output=1
Closed-loop control – performance limits

- Slower response
- Less disturbance rejection

Goal: Keep Output=1

Closed-loop system without time-delay

Closed-loop system with time-delay
Closed-loop control – performance limits

Summary

- Time-delay adversely affects obtainable closed-loop performance – no matter which controller is applied
- Time-delays within the subsurface system itself cannot be changed
- Workflow and tool-based induced time-delays should be understood and managed
Closed-loop vs. Open-loop control

Linear system:\[ \frac{dx(t)}{dt} = Ax(t) + Bu(t), \quad x(0) = x_0 \]

Input trajectory 1: \( u(t) = g(x(t)) = Gx(t) \)
\[ \frac{dx(t)}{dt} = Ax(t) + Bu(t) = Ax(t) + Bg(x(t)) = (A + BG)x(t) \]

Input trajectory 2: \( u(t) = h(t; x(t_0)) \)
\[ \frac{dx(t)}{dt} = Ax(t) + Bu(t) = Ax(t) + Bh(t; x(t_0)) \]

Observation: Open-loop control cannot change system dynamics – In particular open-loop control cannot stabilize an unstable system
Stabilizing a system by closed-loop control
- Casing-heading (slugging) in gas-lift wells

Two options
- Reduce choke opening (more friction) to stabilize flow
- Introduce closed-loop control
Stabilizing a system by closed-loop control

Closed-loop control increased production by 6%

Closed-loop vs. Open-loop control in reservoir management

**Input trajectory 1:** $u(t) = g(x(t))$

**Input trajectory 2:** $u(t) = h(t; x(t_0))$

**Open-loop control** in reservoir management:
- History-matched model with data until June 2005
- Optimize production strategy for next three years
- Implement production strategy

**Closed-loop control** in reservoir management:
- History-matched model with data until June 2005
- Optimize production strategy for next three years
- Implement production strategy
- Collect output data and update model "often"
- Re-adjust the production strategy "often"
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MPC - principle

- Past
- Set-point

State $x(t)$

Input $u(\cdot)$

Time
MPC - principle

state $x(\cdot)$

input $u(\cdot)$

past

future

prediction horizon

set-point

$t$

$t + T_P$

Time
MPC - principle

\[
\min_{u(\cdot)} J(u(\cdot); x(t)) = \int_{t}^{t+T_p} F(x(\tau), u(\tau)) d\tau
\]

s.t.

\[
\frac{dx(\tau)}{dt} = Ax(\tau) + Bu(\tau), \quad \tau \in [t, t+T_p]
\]

\[
x(t) = x_t
\]

\[
u \leq u(\tau) \leq \bar{u}, \quad \tau \in [t, t+T_p]
\]
MPC - principle

Past\hspace{1cm} future\hspace{1cm} prediction horizon\hspace{1cm} set-point

tate $x(t)$\hspace{1cm} predicted state\hspace{1cm} optimal input $u$ at time $t$

input $u(\cdot)$

$t$\hspace{1cm} $t + T_P$\hspace{1cm} Time
MPC - principle

past

set-point

state $x(\cdot)$

input $u(\cdot)$

$t$

$t + \delta$

Time
MPC - principle

state $x(\cdot)$

input $u(\cdot)$

$past$

$t$ $t + \delta$

set-point

Time
Model Predictive Control (MPC) offers a compromise between strategy 1 and 2.

Open-loop control

Input trajectory 2: \( u(t) = h(t; x_0) \)

Closed-loop control

Input trajectory 1: \( u(t) = g(x(t)) \)
Model Predictive Control (MPC)

- It all started in the late 70’s (Cutler, Richalet)
- Simple step-response models + simplified QP-algorithms
- Problems have become larger, models have become more detailed, and there are 10,000++ applications out there
- Consistent constraint handling is an important reason for success.
- The use of MPC for RT decision making has been a game-changer in the process industries
  - Refineries, petrochemicals, chemical, pulp and paper,…
- High performance MPC-applications using nonlinear physics-based models with nonlinear state and parameter estimation filter and SQP-like optimizers is spreading

Will continue with some important MPC issues
- Prediction horizon
- State and parameter estimation
- Model complexity
A subtle point for the finite prediction case: The predicted open-loop trajectories are not equal to closed-loop trajectories even in the (ideal) nominal case.

Too short prediction horizon may give an unstable system.

The prediction horizon must capture the dominant dynamics.
MPC - state and parameter estimation

- Challenging MPC applications necessitates the use of nonlinear filters – beyond the Extended Kalman Filter (EKF).
- Two trends are apparent
  - Optimization-based filters – Moving horizon estimation
  - Higher order recursive filters – Unscented Kalman Filter

A theoretical justification

Guaranteed Margins for LQG Regulators
JOHN C. DOYLE

Abstract—There are none.

IEEE TRANSACTIONS ON AUTOMATIC CONTROL, VOL. AC-23, NO. 4, AUGUST 1978

A practical justification
- Aluminum production
- A nonlinear filter is critical for good performance

/Reference: Kolaas et al (2008)/
Unscented Kalman Filtering - principle

- **Compute sigma points** (initial state estimates $\hat{x}_0$) by using the expected value and covariance for the states $x_0$, and if applicable the process noise $q_0$ and measurement noise $v_0$

  - **Prediction**: Compute prior state estimates by propagating each sigma point using the model

  - **Filtering**: Compute aposteriori estimate

  $$\tilde{x}_{k+1} = \hat{x}_{k+1} + K_{k+1} (y_{k+1}^{obs} - g(\hat{x}_{k+1}))$$

  $$\tilde{P}_{x,k+1} = \hat{P}_{x,k+1} - K_{k+1} \hat{P}_{y,k+1} K_{k+1}^T$$

---

Unscented Kalman Filtering - principle

- Compute new sigma points (state estimates) by using the expected value and covariance for the states $x_{k+1}$, and if applicable the process noise $q_{k+1}$ and measurement noise $v_{k+1}$
- Continue propagation of each ensemble member

Note
- The sigma points are computed according to a fixed procedure
- New sigma points are computed at each time step
Unscented Kalman Filter - discussion

- Applications are reported in aerospace and aircraft engineering, process control and financial applications among others.
- Motivation – increased accuracy in predicting stochastic properties (mean and covariance).
- Constraint handling is an important issue in process control.
- Increased computation since several sigma points ("particles") are propagated forward in time.
- An issue is the trade-off between accuracy and the number of sigma points.
Closed-loop control – model complexity

- Closed-loop control usually relies on surprisingly simple models
- The PID-controller – the workhorse in control – assumes that processes can be modelled by a 2.order system with the following typical step response.

![Diagram of step response for a 2nd order system](image.png)
A simple model for complex dynamics: Closed-loop control of casing-heading in gas-lift wells

- Only surface data available
- Dynamic well model
- Estimate of downhole pressure
- Use estimate in the same controller as before

Model complexity for the state estimator?

Example: Closed-loop control - experimental results

There is a bias here - is this a problem?
Can the optimal control problem be realized by a structure in which the estimator and the control calculation are separated?

- No, because the separation property does not hold for nonlinear partially unknown systems.
- The separation property only holds for some very special cases.
Dual control – a forgotten property

A controller may have a dual function:
- **Excite the system to reduce uncertainty**
  
  => Dual control (Feldbaum, 1960)
- Results in a stochastic adaptive control problem – which is unsolvable in practice
- An optimal controller will exploit the dual control effect. Hence, it implicitly needs information on the data assimilation method when computing the control

The purpose of closed-loop control is to:
- Disturbance rejection
- Follow a reference trajectory
- Stabilize unstable systems
Dual control and informative excitation

Standard parameter estimation problem

\[ J(\theta) = \sum_{i=1}^{n} \left\| y_{i}^{\text{obs}} - y_{i}(\theta) \right\| \]

\( \theta \) – unknown parameters

- The Hessian \( H(\theta) = \nabla_{\theta \theta} J(\theta) \) provides a measure of parameter uncertainties
- \( H(\theta) \) depends on the control input \( u \)

Input design formulation

\[ \min_{q \in Q} (\lambda_{\max} H^{-1}(\theta) + \alpha \kappa(H)) \]

\( \lambda \) – eigenvalue

\( \kappa \) – condition number

\( q \) – input parametrization

Example: Production from multiple wells

- Optimize on the time instances in which step changes occur in three different wells

Results

- Parameter variance may decrease by 50% by clever excitation

Reference: Foss (1990) – SPE 18402/
Closed-loop reservoir management challenging the present structure

- Can the optimal control problem be realized by a structure in which the estimator and the control calculation are separated?
  - No, because the separation property does not hold for nonlinear partially unknown systems
  - The separation property only holds for some very special cases.

![Diagram](image-url)
Process industries
There exists an established real-time control/optimization hierarchy

<table>
<thead>
<tr>
<th>Length of decision horizon</th>
<th>Real Time Optimization (RTO)</th>
<th>Model Predictive Control (MPC)</th>
<th>Control/automation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Day</td>
<td>Open-loop Whole plant Static physics-based model</td>
<td>Closed/open-loop Unit level Dynamic physics-based or empirical model</td>
<td>Closed-loop Sub-unit level PID-control</td>
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<td>Hour</td>
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Note: APC is often used for "Advanced Process Control". MPC is a subset of APC.
### How does the hierarchy relate to petroleum production

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<td><strong>Years</strong></td>
<td>Life-cycle optimization</td>
<td>Production optimization</td>
<td>Dynamic optimization</td>
<td>Automatic control</td>
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<td></td>
<td>maximizing recovery and/or NPV</td>
<td>of subsurface and</td>
<td>- MEG loops (few applications</td>
<td>loops – compressor,</td>
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<td></td>
<td>production facilities</td>
<td>exist)</td>
<td>flow, pressure</td>
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<td>(some applications exist -</td>
<td></td>
<td>(common practice)</td>
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<td>GAP)</td>
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Closed-loop reservoir management – summing up

- Use MPC as the over-arching concept for decisions making
- All technologies must be embedded into work flows
- Move from qualitative to quantitative descriptions
- Computational integration is essential
- Standardize a RT control hierarchy for reservoir management
- Decomposition methods exploiting structure
- Massively parallel computing
- Time-delay-relate to it
- Explore the use of simple proxy models
- Explore the dual control property
- Reduce uncertainty
- Reinforce the feedback loop in a balanced way according to the weakest link thinking
- Use MPC as the over-arching concept for decisions making
- Standardize a RT control hierarchy for reservoir management
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- Reinforce the feedback loop in a balanced way according to the weakest link thinking
Closed-loop reservoir management – a control perspective

Typical for the subsurface domain

- Large models
  - Much simpler (proxy) models should be explored to a much larger degree
- Large uncertainties
  - Data quality is improving, data quantity is increasing and delays are reduced
  - Data assimilations methods is clearly important
  - Just as important: Work flows which embed model-based technologies
- Open-loop and closed-loop control
  - There are unnecessary long delays in the adjusting production strategies increasing the time-delay of the closed-loop and thereby reducing performance
- Informative data is valuable. Information content is a function of instrumentation and excitation
- Noe om IO og prog.2 planer (streamline)
Closed-loop and feedforward control

Linear system: \[ \frac{dx(t)}{dt} = Ax(t) + Bu(t) + Cv(t), \quad x(0) = x_0 \]

Input trajectory 1: \( u(t) = g(x(t)) = Gx(t) \)

\[ \frac{dx(t)}{dt} = Ax(t) + Bu(t) + Cv(t) = (A + BG)x(t) + Cv(t) \]

Input trajectory 3: \( u(t) = Gx(t) + Hv(t) \)

\[ \frac{dx(t)}{dt} = Ax(t) + Bu(t) + Cv(t) = (A + BG)x(t) + (C + BH)v(t) \]

Observation: Combining closed-loop and feedforward control makes sense
Closed-loop vs. Open-loop control and feedforward control

Linear system: \[
\frac{dx(t)}{dt} = Ax(t) + Bu(t) + Cv(t), \quad x(0) = x_0
\]

Input trajectory 1: \[u(t) = g(x(t)) = Gx(t)\]

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Input trajectory 2: \[u(t) = h(t; x_0)\]

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Input trajectory 3: \[u(t) = Gx(t) + Hv(t)\]

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Observation: Combining closed-loop and feedforward control makes sense

External disturbance
Closed-loop control
Open-loop control
Closed-loop + feedforward control
Closed-loop control – performance limits

- Feedback loop performance is limited by the dynamic response between control inputs and output data.
- Long time-delays are particularly harmful to performance.
  - Tight control is not possible => Unstable feedback loop

Diagram:
- Control law
- Control inputs
- System
- Output data
- C issues
Closed-loop vs. Open-loop control

Feedback control

Control law 1

Control inputs → System → Output data

Feedforward control

Exogenous data

Control law 2

Control inputs → System → Output data

Feedback and feedforward control are often combined

Open-loop control in reservoir management
- History-matched model with data until sept 2006
- Optimize production strategy for next two years
- Implement production strategy

Closed-loop control in reservoir management
- History-matched model with data until sept 2006
- Optimize production strategy for next two years
- Implement production strategy
- Collect output data
- Re-optimize production strategy every month
Ensemble Kalman Filtering - principle

Discrete model
\[
x_{k+1} = f(x_k, q_k) \\
y_k = g(x_k) + v_k
\]

- Draw ensemble members (initial state estimates \(\hat{x}_0\)) by sampling from a distribution \(pdf(x_0)\)

- Prediction: Compute prior state estimates by propagating each ensemble member using the model \(\hat{x}_{k+1} = f(\hat{x}_k, \hat{q}_k)\)
The process noise estimate \(\hat{q}_k\) is sampled from a distribution \(pdf(\hat{q}_k)\)

- Compute the mean value and covariance using the prior state estimate of each ensemble member
- Compute Kalman gain \(K_{k+1}\)

- Filtering: Compute a posteriori estimate for each particle \(\tilde{x}_{k+1} = \hat{x}_{k+1} + K_{k+1}(y_{k+1}^{obs} + \hat{v}_{k+1} - g(\hat{x}_{k+1}))\)
The measurement noise estimate \(\hat{v}_{k+1}\) is sampled from a distribution \(pdf(\hat{v}_{k+1})\)
Ensemble Kalman Filtering - principle

- Continue propagation of each ensemble member

Note
- Each ensemble member is propagated individually.
- But - the same Kalman gain is used for all ensemble members