

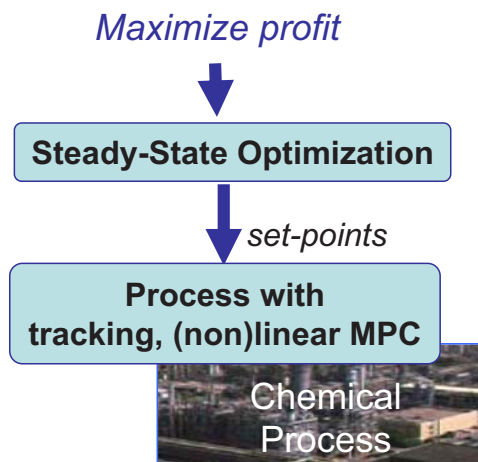
An efficient computational strategy for dynamic real-time optimization

Lynn Würth and Wolfgang Marquardt

Promatch Symposium REDUCIT
Frankfurt, 4 November 2008

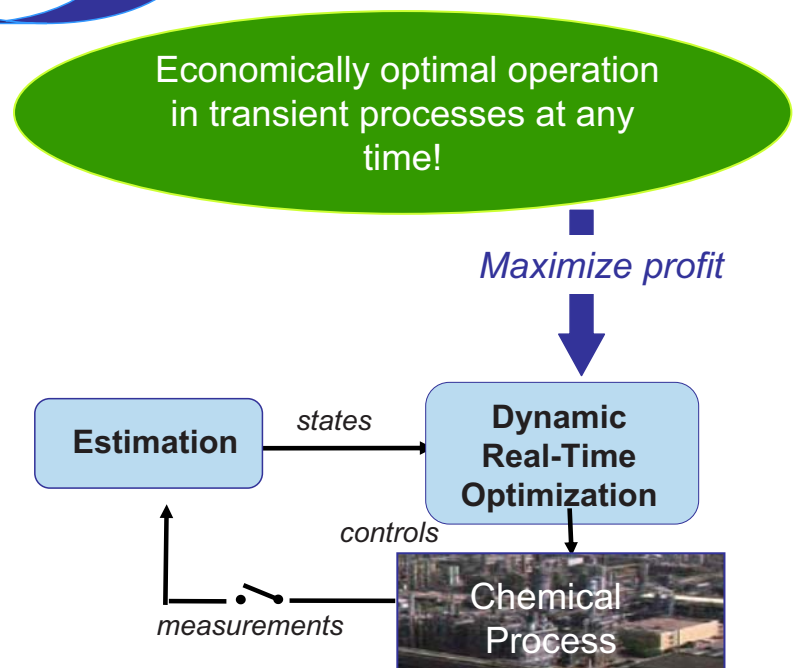
Dynamic Real-Time Optimization

Current set-up for RTO & MPC



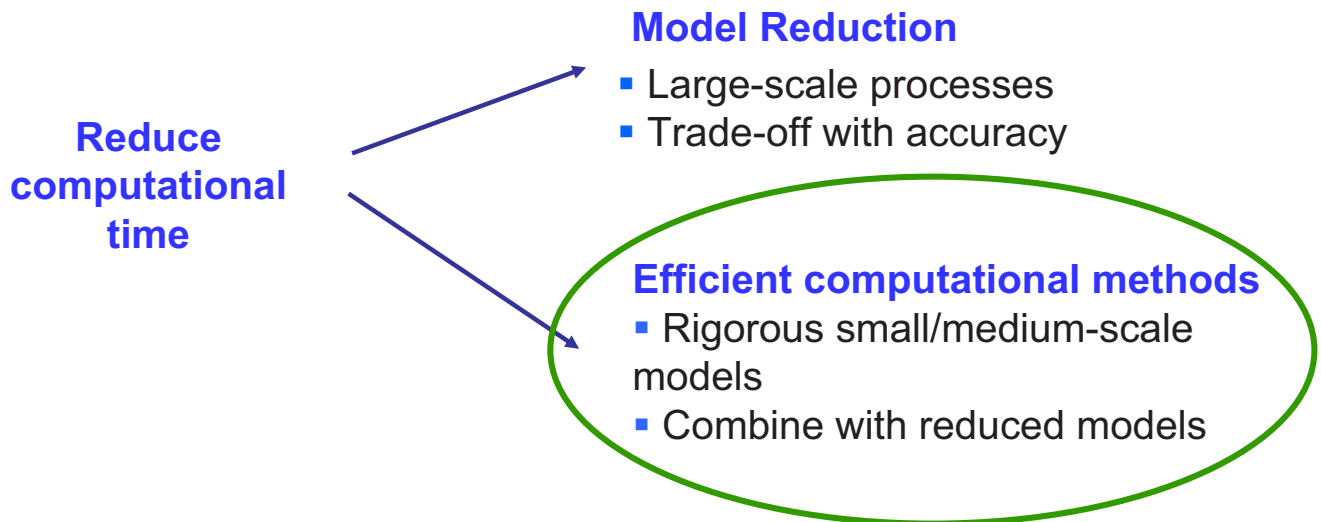
- Inconsistent objectives
- Dynamic degrees of freedom not exploited for profitable operation

Dynamic Real-Time Optimization (DRTO):



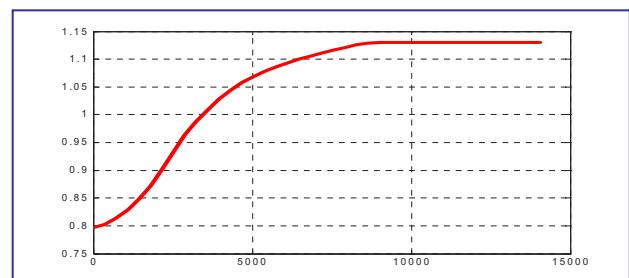
Obtain solutions of dynamic optimization problem in real-time but:

- Large-scale systems, complex models
- Different time-scales
- Severe nonlinearities e.g. reaction kinetics



Neighboring-Extremal Updates

Objective:
Fast updates of optimal trajectory
under uncertainty



Neighboring Extremal Updates: Fast solution of related problem in the neighborhood of a nominal optimal solution

Related methods:

Indirect methods for optimal control: Neighboring extremal feedback law (Bryson and Ho, 1969, Pesch, 1979)

Direct methods: Diehl et al., 2002: Real-time iterations
Kadam and Marquardt, 2004: Sensitivity-based updates
Zavala and Biegler, 2008: Advanced-step NMPC

Optimization problem formulation on receding horizon:

	$\min_{\mathbf{u}^j(t)} \Phi(\mathbf{x}(t), \mathbf{u}^j(t), t_0, t_f)$	<i>Economic objective function</i>
s.t.	$\dot{\mathbf{x}}(t) = \mathbf{f}(\mathbf{x}(t), \mathbf{u}^j(t), \mathbf{d}^j(t), \hat{\boldsymbol{\theta}}),$ $\mathbf{y}(t) = \mathbf{g}(\mathbf{x}(t), \mathbf{u}^j(t), \mathbf{d}^j(t), \hat{\boldsymbol{\theta}}),$ $\mathbf{x}(t^j) = \hat{\mathbf{x}}^j,$	$\left. \begin{array}{l} \text{DAE system (process model)} \\ \text{initial conditions} \end{array} \right\}$
	$\mathbf{0} \geq \mathbf{h}(\mathbf{x}(t), \mathbf{y}(t), \mathbf{u}^j(t)),$	<i>path constraints</i>
	$\mathbf{0} \geq \mathbf{e}(\mathbf{x}(t_f^j)),$	<i>endpoint constraints</i>
	$t \in [t^j, t_f^j],$	<i>time horizon</i>
	$t^j := t^{j-1} + \Delta t$	<i>horizon shift (index j)</i>

Reformulation of the infinite-dimensional problem

- Control vector parameterization (single-shooting)

$$\mathbf{u}_i(t) \approx \sum_{k \in \Lambda_i} z_{i,k} \phi_{i,k}(t)$$

- Collect different uncertainties in vector \mathbf{p} :

- Model uncertainties $\hat{\boldsymbol{\theta}}$
- Disturbances $\mathbf{d}(t)$ parametrized by \mathbf{c}^j
- Estimated state variables $\hat{\mathbf{x}}^j$

$$\mathbf{p} = (\mathbf{c}^j, \hat{\boldsymbol{\theta}}, \hat{\mathbf{x}}^j) \in \mathbb{R}^{n_p}$$

- Reformulation as nonlinear parametric program problem (NLP)**

$$\begin{array}{l} \min_{\mathbf{z}, t_f} \Phi(\mathbf{z}, \mathbf{p}) \\ \text{s.t. } \mathbf{0} \geq \mathbf{g}(\mathbf{z}, \mathbf{p}) \\ \mathbf{0} \geq \mathbf{e}(\mathbf{x}(t_f)) \end{array}$$

DAE system is solved by underlying numerical integration

Sensitivity-based updates

Idea: Exploit sensitivity information of offline/previously solved optimization problem to generate a fast approximation of the optimal update (Fiacco, 1983)

Solve Quadratic Program online (Kadam and Marquardt, 2004)

$$\begin{aligned} \min_{\Delta z} \quad & \frac{1}{2} \Delta z^T L_{zz}(p_0) \Delta z + \Delta p^T L_{pz}(p_0) \Delta z + f_z(p_0) \Delta z \\ \text{s. t.} \quad & g(p_0) + g_z(p_0) \Delta z + g_p(p_0) \Delta p \geq 0 \end{aligned}$$

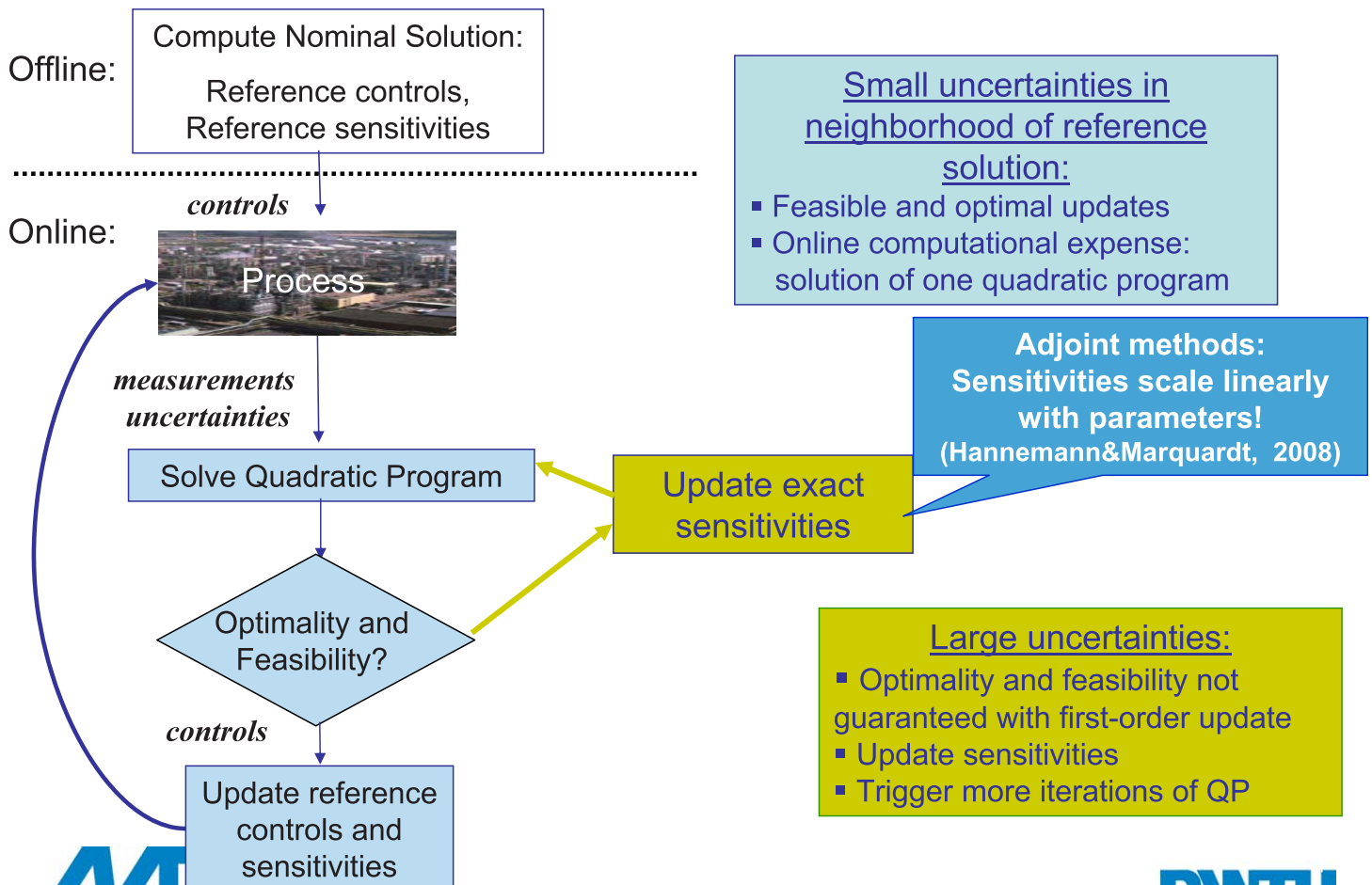
*L: Lagrange function
g: constraints*

Parametric uncertainty: $\Delta p = p - p_0$

Sensitivities are computed at the nominal parameter p_0

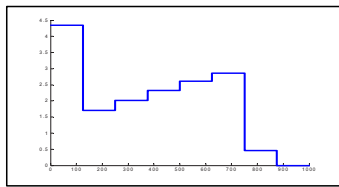
➔ Fast first-order prediction of optimal controls & update of active constraints

Algorithm for online trajectory updates

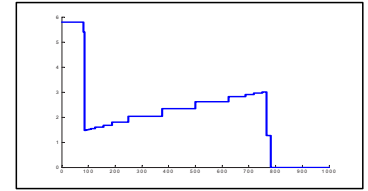
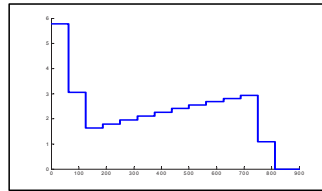


Grid refinement strategy

Offline adaptation



Wavelet
Analysis
→
Reoptimi-
zation

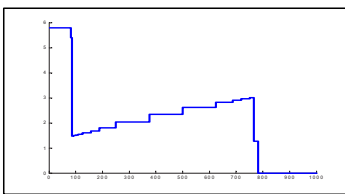


(Schlegel et al., 2005)

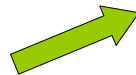
➔ Reduction of degrees of freedom while maintaining solution accuracy!

Online adaptation under uncertainties:

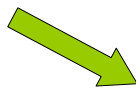
Adapted profile



Similar profile



- Small number of degrees of freedom
- **Fast computation**



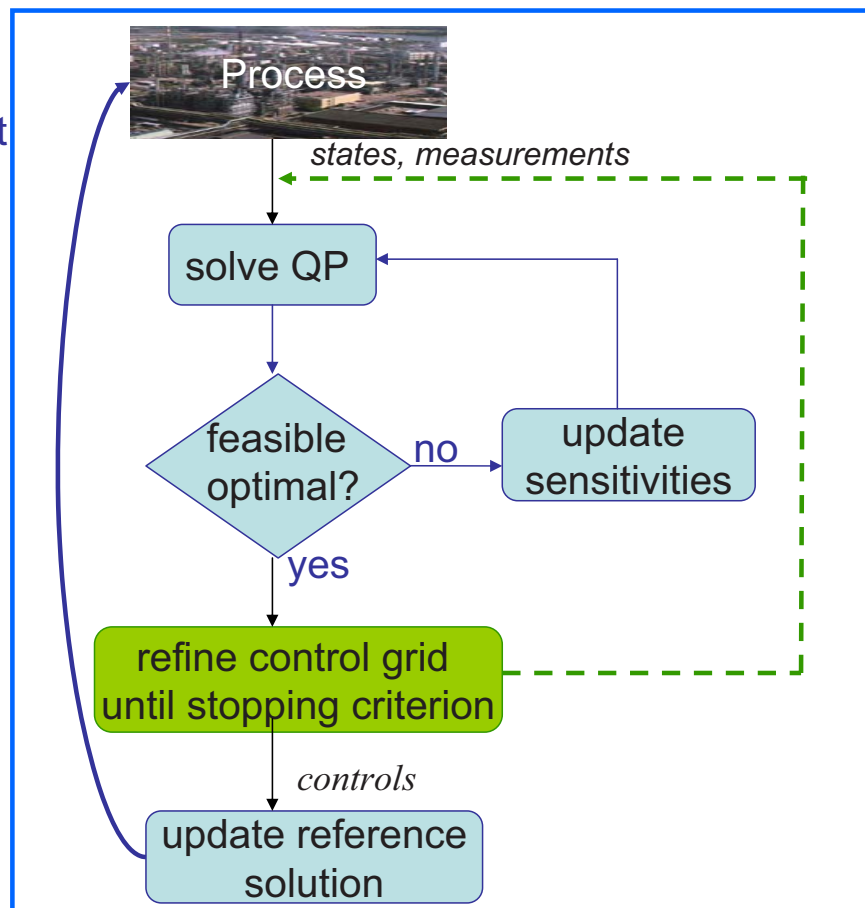
Change in profile

- Sensivity-based update on previous grid not sufficient
- **More iterations** to detect new profile

Online adaptation of control grid

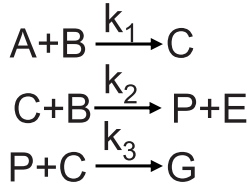
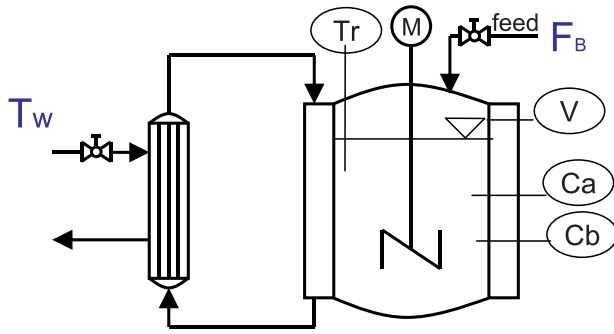
Implementation of grid refinement in the online algorithm:

Refinement of solution if time is available



Example 1: Real-time optimization of semi-batch reactor

Williams-Otto Benchmark Example



Operational Objective:
Maximize Product P

Optimization problem formulation

$$\begin{aligned}
 &\max_{F_{B_{in}}(t), T_w(t)} \text{Yield}(t_f) \\
 &\text{s.t. process model} \\
 &0 \leq F_{B_{in}}(t) \leq 5.784 \frac{\text{kg}}{\text{sec}}, \\
 &20 \leq T_w(t) \leq 100 \text{ }^\circ\text{C}, \\
 &60 \leq T_r(t) \leq 90 \text{ }^\circ\text{C}, \\
 &0 \leq V(t_f) \leq 5 \text{ m}^3.
 \end{aligned}$$

Uncertainties

$$\begin{aligned}
 k_i &= a_i \exp\left(\frac{-b_i}{T_r + 273.15}\right), i = 1, \dots, 3 \\
 b_{1,0} &= 6.6667 \text{ sec}^{-1} \\
 T_{in} &= 35 \text{ }^\circ\text{C} \\
 p &:= [T_{in}, b_1, \hat{x}]
 \end{aligned}$$



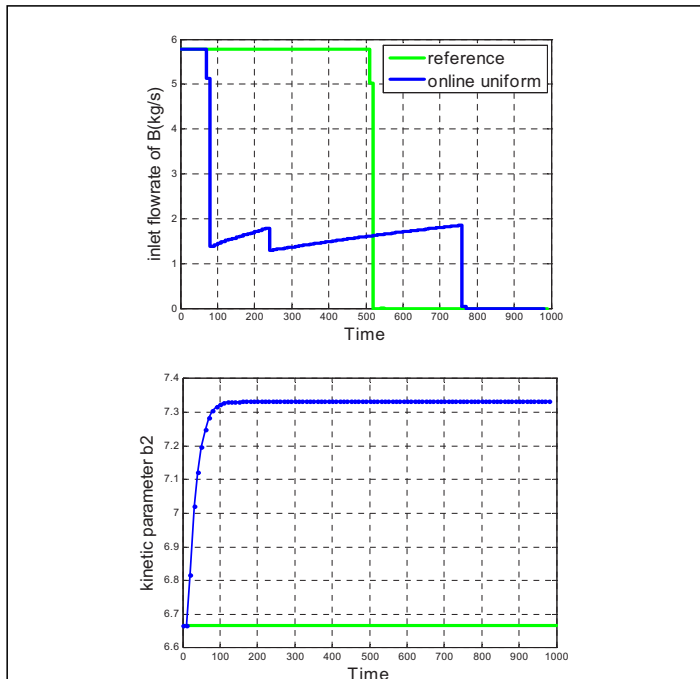
State estimation with EKF, sampling time of 10 s.



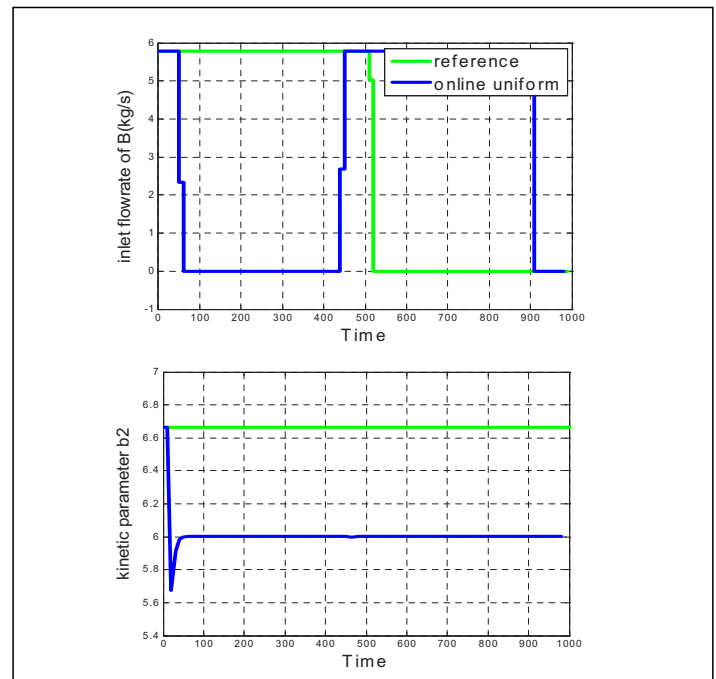
11

Real-time optimization results

Initial condition for kinetic parameter +10%



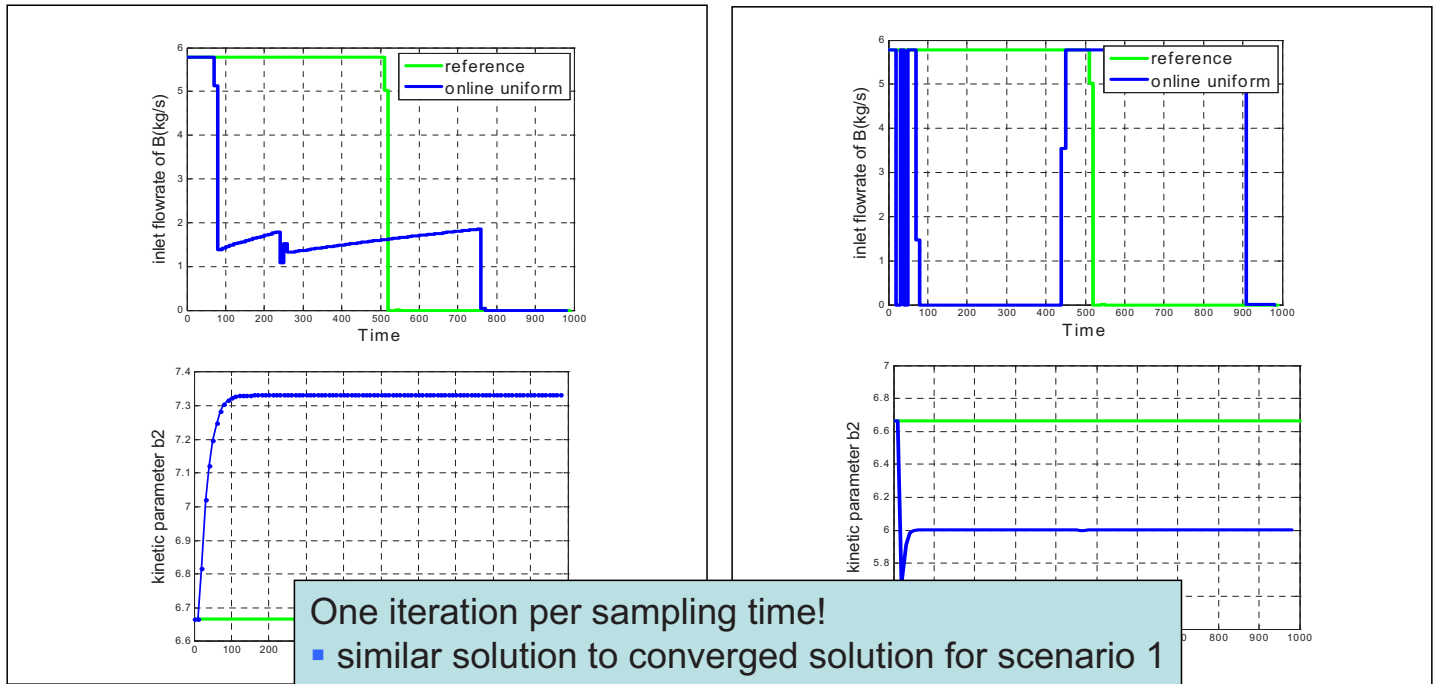
Initial condition for kinetic parameter -10%,



Comparison with online iterations

Initial condition for kinetic parameter +10%

Initial condition for kinetic parameter -10%,

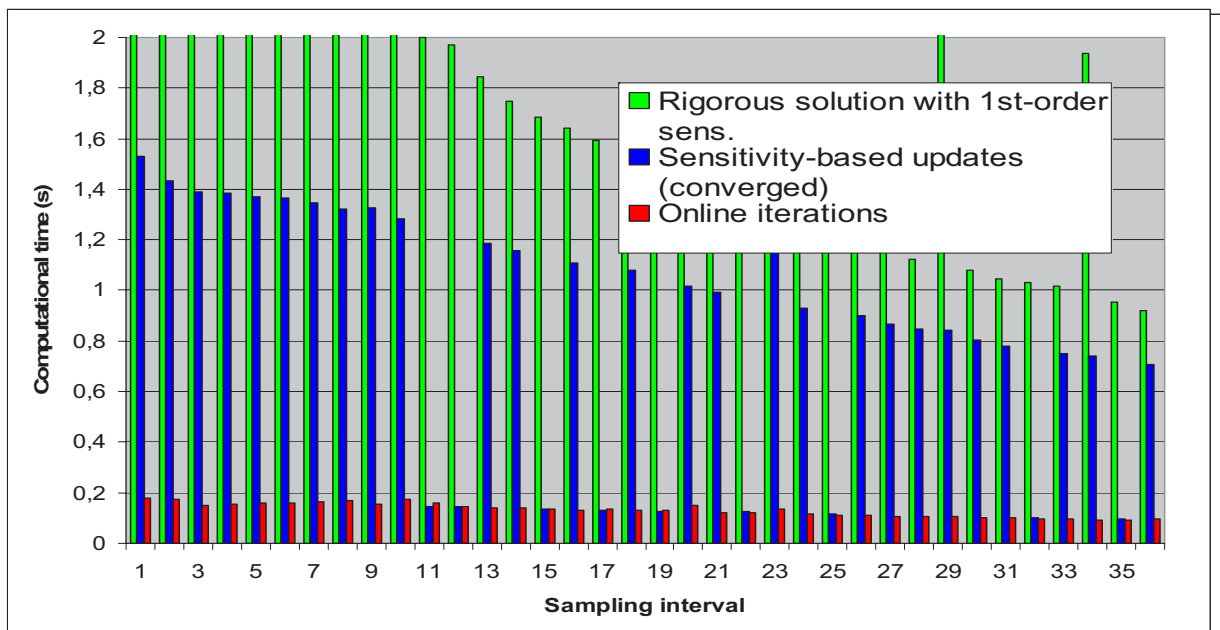


One iteration per sampling time!

- similar solution to converged solution for scenario 1
- oscillations observed for scenario 2

Comparison of computational performance

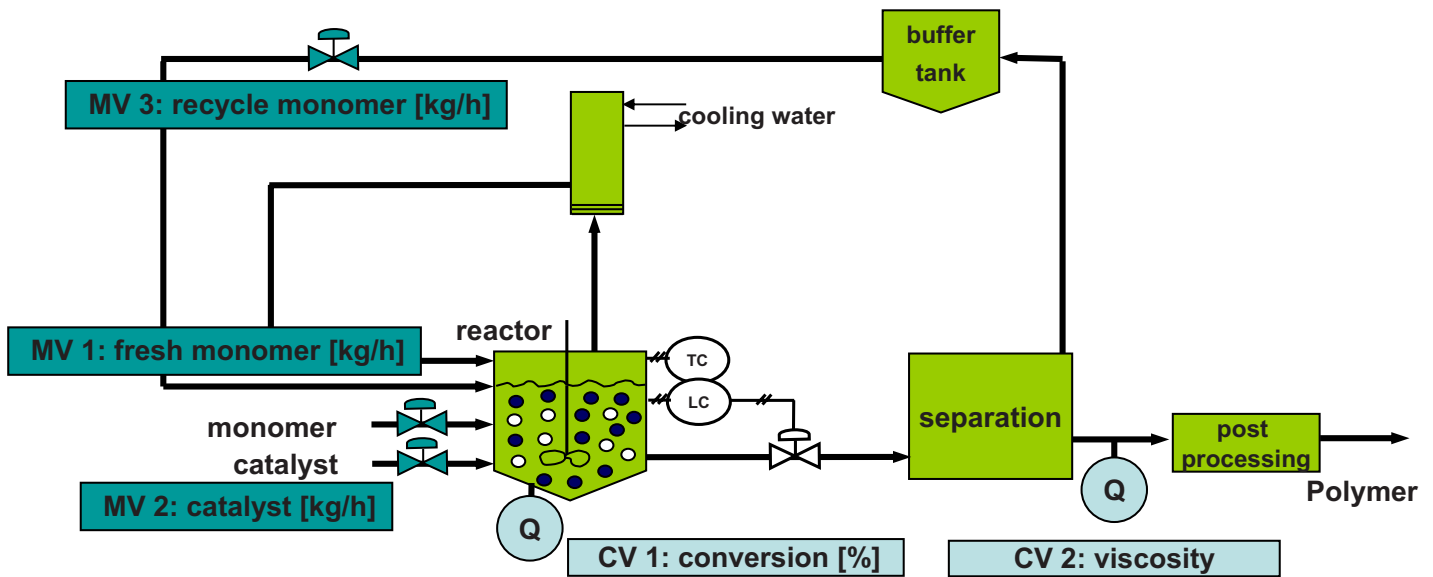
- Compared to rigorous solution with first order sensitivities
- Sensitivity-based updates with second-order exact sensitivities
 - ➡ fast convergence
- Online iterations: computational effort very low



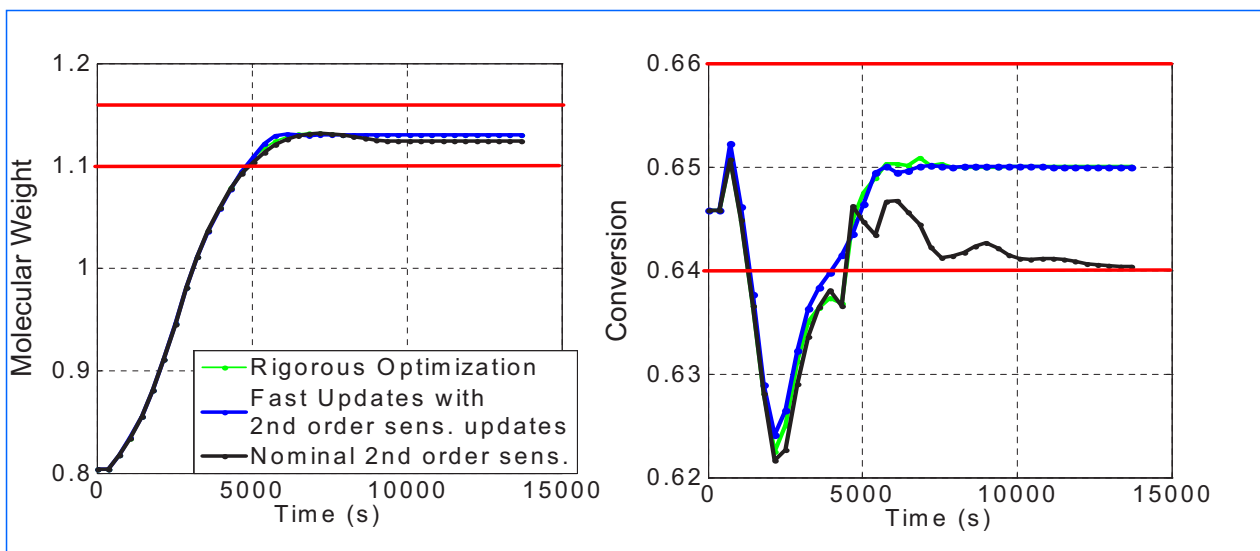
Example 2: Copolymerization Reactor

- complex reaction mechanism
- large-scale model (~ 2000 equations)
- 3 control variables, 6 path constraints

- process operations tasks:
- optimal load change
 - optimal grade change



Results with Fast Updates



Fast updates with online update of 2nd order sensitivities:

=> **Close to rigorous optimal solution**

- Method based on neighboring extremal updates was presented
 - Fast convergence
 - Solution accuracy is adjusted by a trigger

- Control performance:
 - Trade-off between computational delay and solution accuracy
 - Adjust number of iterations

- Adaptation:
 - Grid refinement allows reduction of degrees of freedom
 - Automatic structure detection => minimum number of parameters

Acknowledgments

Financial support from Marie-Curie Research Training Network PROMATCH funded by the European Commission (MRTN-CT-2004-512441) and the German Research Foundation DFG (MA 1188/28-1) is gratefully acknowledged