Nonlinear Model Predictive Control of a Bubbling Fluidized Bed Adsorber for Post-Combustion Carbon Capture

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Outline

- Introduction
  - Bubbling fluidized bed (BFB) adsorber
- Model reduction of the BFB adsorber
  - Temporal model reduction
  - Spatial model reduction
- Nonlinear model predictive control (NMPC) of the BFB adsorber
  - NMPC using reduced model
  - NMPC with input and state blocking
  - Online-control of the BFB adsorber
- Conclusions and future work

Introduction

Bubbling Fluidized-Bed Adsorber

- Bubbling fluidized bed (BFB) adsorber
  - Solid-sorbent-based post-combustion carbon capture system
  - Optimal operation to improve environmental and economic performance
- One-dimensional three-region, non-isothermal BFB model [1]
  - Differential equations

    Mass and energy balances for 6 components in three regions

$$\frac{\partial n_{e,x}}{\partial t} A(1-a_x\delta_x-\delta_x)(1-\varepsilon_x)\rho_s = \frac{\partial J_x n_{e,x}}{\partial x} + K_{s,bulk,x} + A\delta_x\rho_s K_{ce,x}(n_{c,x}-n_{e,x}) + A(1-a_x\delta_x-\delta_x)(1-\varepsilon_x)r_{e,x}$$

  - Algebraic equations

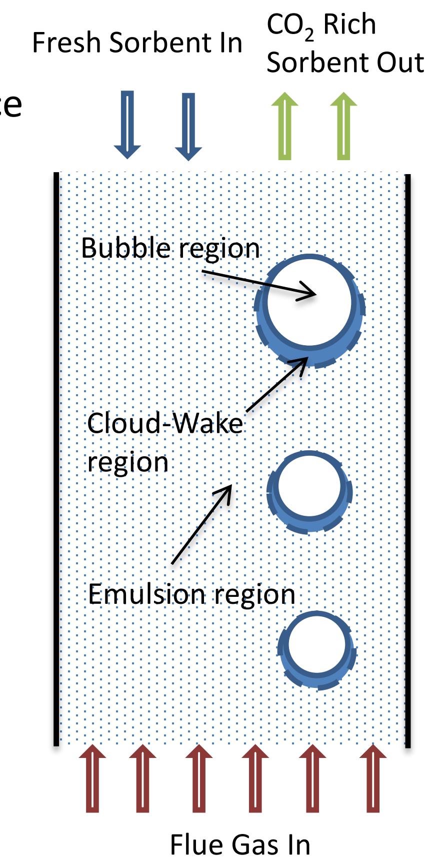
    Hydrodynamic correlations — Mass and heat transfer coefficients

    Gas phase properties — Heat exchanger tube correlations

$$\left(\frac{d_{b,u,x}^{0.5}-d_{b,e,x}^{0.5}}{d_{b,0}^{0.5}-d_{b,e,x}^{0.5}}\right)^{1-\gamma_1/\gamma_{3,x}} \left(\frac{d_{b,u,x}^{0.5}-\gamma_{2,x}^{0.5}}{d_{b,0}^{0.5}-\gamma_{2,x}^{0.5}}\right)^{1+\gamma_1/\gamma_{3,x}} = e^{-0.3x/D_t}$$

$$K_{ce,x} = 6.78\left(\frac{\varepsilon_x^{2} D_x v_{b,x}}{d_{b,x}}\right)^{0.5}$$

  - Highly nonlinear, large-scale differential and algebraic equation system with **14187** equations (**1994** differential equations)



[1] Lee, A., & Miller, D. C. (2012). A one-dimensional (1-d) three-region model for a bubbling fluidized-bed adsorber. *Industrial & Engineering Chemistry Research*,*52*(1), 469-484.

Introduction

Technology Roadmap

- BFB adsorber: spatially distributed first-principle model

  + Accurate

  - Computationally expensive

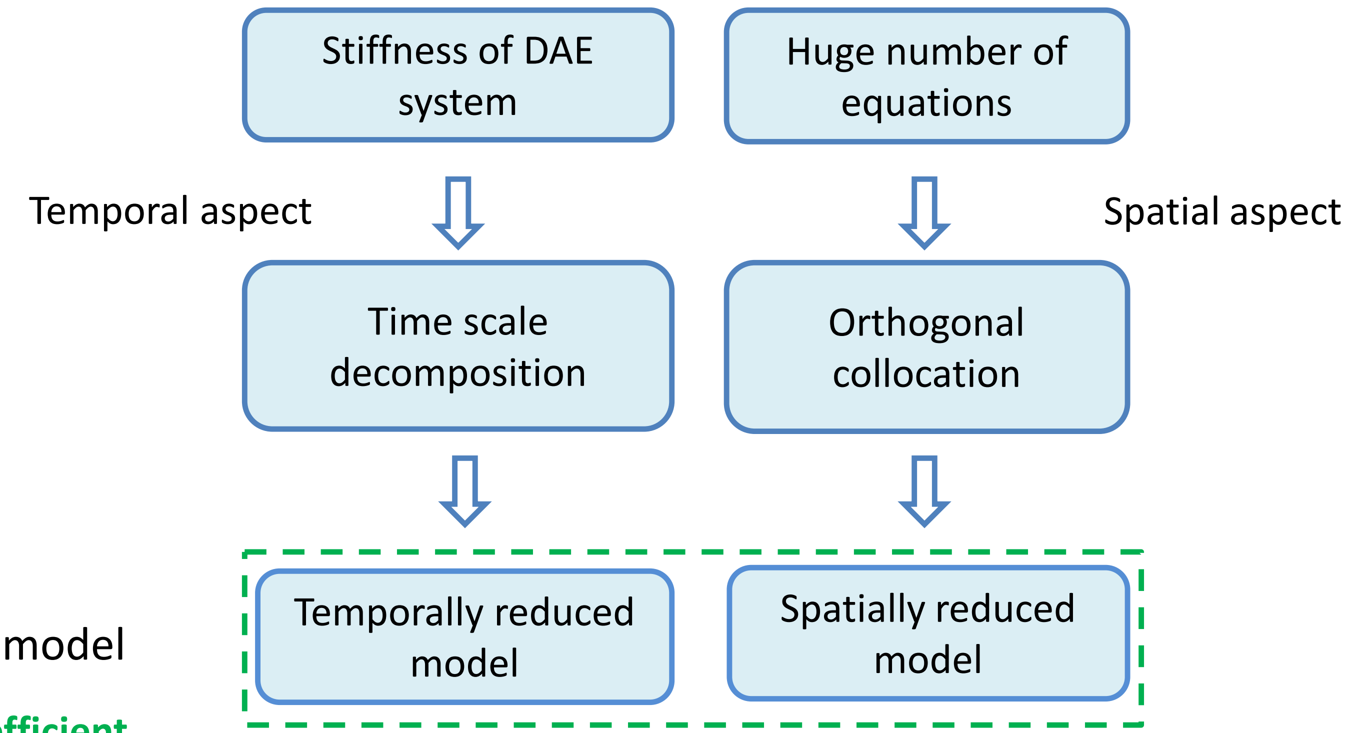
- Possible reasons

- Model reduction approaches

- Dynamic reduced model

  + Computationally efficient

  + Capture the dynamics of rigorous model



Dynamic reduced models for BFB adsorber [2]

- Temporal model reduction
  - Remove fast equilibrium reaction using nullspace projection method
  - BFB model reaction kinetics

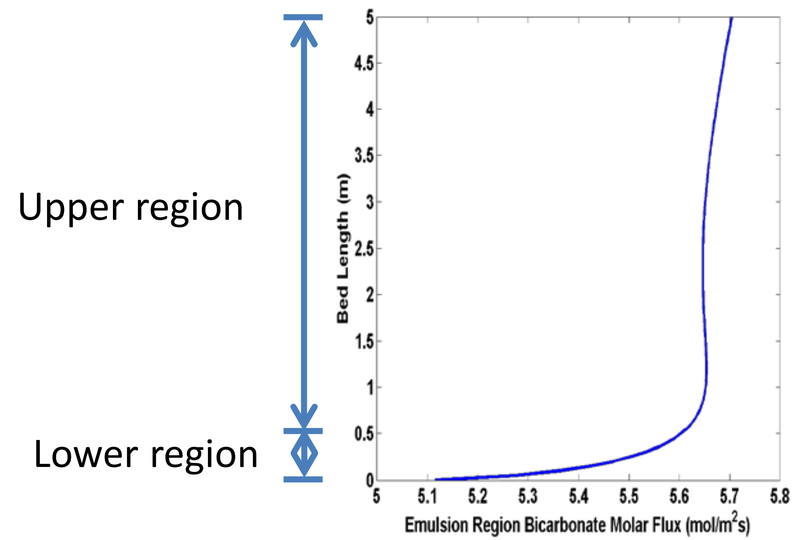
$$H_2O_{(g)} \rightleftharpoons H_2O_{(phys)}$$

$$2R_2NH + CO_2 \rightleftharpoons R_2NH_2^+ + R_2NCO_2^-$$

$$R_2NH + CO_2 + H_2O_{(phys)} \rightleftharpoons R_2NH_2^+ + HCO_3^-$$

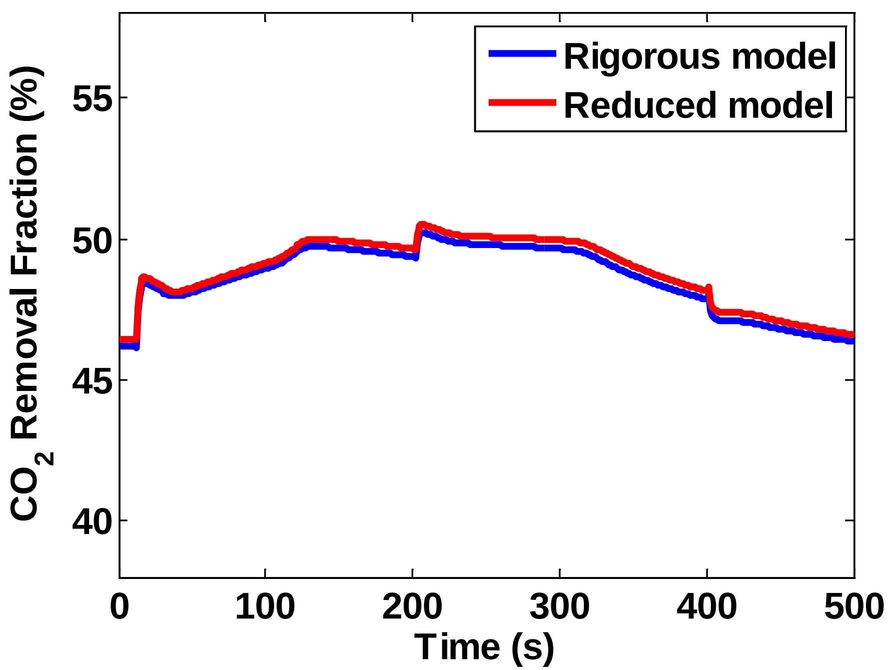
	r_f (mol/m^{3}s)	r_b (mol/m^{3}s)
Reaction 1	10^6	10^6
Reaction 2	10^0	10^0
Reaction 3	10^{-1}	10^{-1}

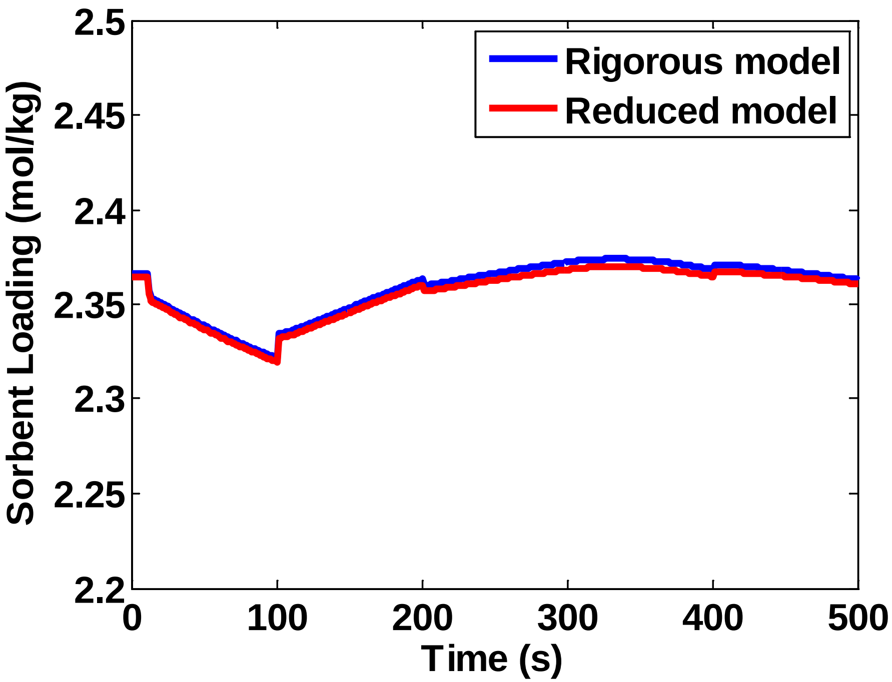
- Spatial model reduction
  - Orthogonal collocation on finite elements
  - Unevenly distributed finite elements based on system's characteristics



[2] Yu, M., Miller, D. C., & Biegler, L. T. (2015). Dynamic reduced order models for simulating bubbling fluidized bed adsorbers. *Industrial & Engineering Chemistry Research*, *54*(27), 6959-6974.

Simulation results
Comparison between rigorous and reduced model





	Model size	Simulation time	MRE1	MSE1	MRE2	MSE2
Rigorous model	14187	193s				
Reduced model	5338	64s	0.68%	0.072	0.18%	9.91e-6

- Tested on an Intel i7-3770 3.40 GHz PC

MRE – Maximum Relative Error
MSE – Mean Squared Error

1 – CO_2 Removal Percent
2 – Sorbent Loading

~65% reduction in simulation time

NMPC using dynamic reduced model

- Nonlinear model predictive control (NMPC) formulation

$$\min_{v} \quad \Psi(z_N) + \sum_{l=0}^{N-1} \psi(z_l, v_l)$$

$$s.t. \quad z_{l+1} = f(z_l, v_l)$$ → Nonlinear process model

$$c_l \le C(z_l, v_l) \le c_u$$ → Process constraints

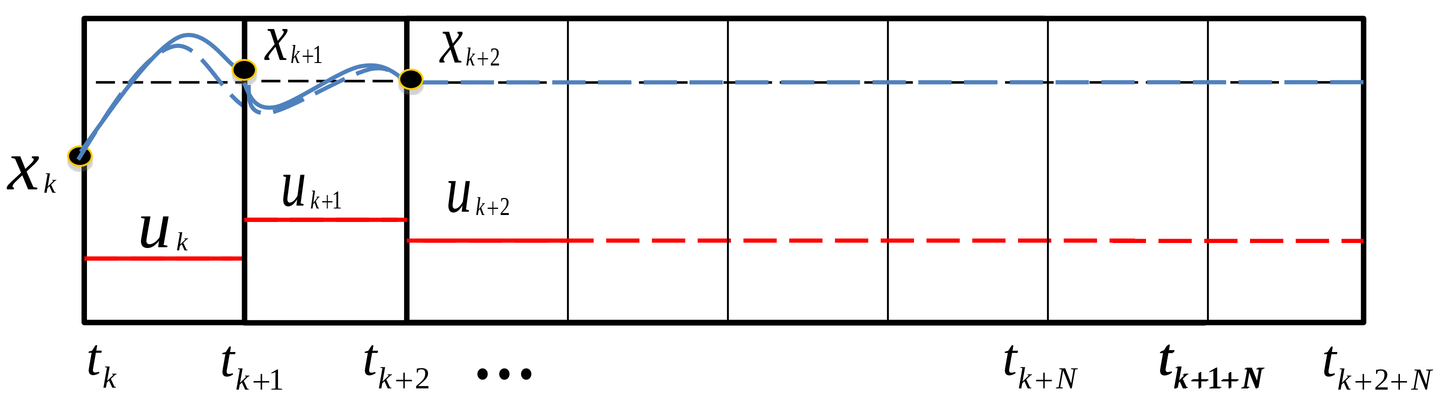
$$z_0 = x(t_k)$$

Nonlinear reduced process model

Model mismatch

Real process/rigorous model

- Output additive correction is used to achieve offset-free control performance



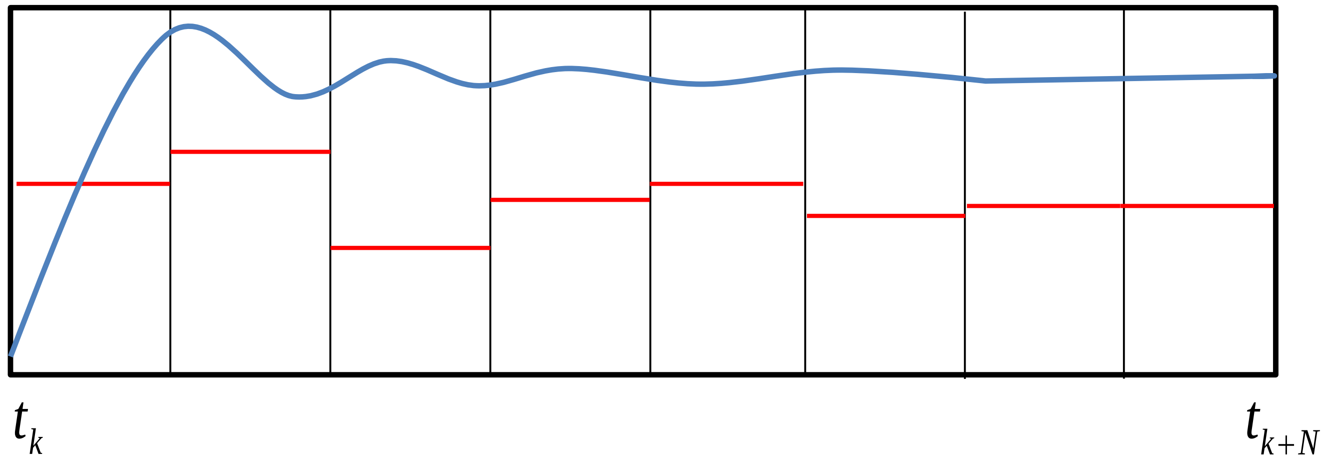
NMPC with nonuniform grids

- NMPC formulation

$$\min_{v} \quad \Psi(z_N) + \sum_{l=0}^{N-1} \psi(z_l, v_l)$$

$$\begin{aligned} s.t. \quad & z_{l+1} = f(z_l, v_l) \\ & c_l \le C(z_l, v_l) \le c_u \\ & z_0 = x(t_k) \end{aligned}$$

- NMPC temporal discretization



NMPC with nonuniform grids

- NMPC formulation

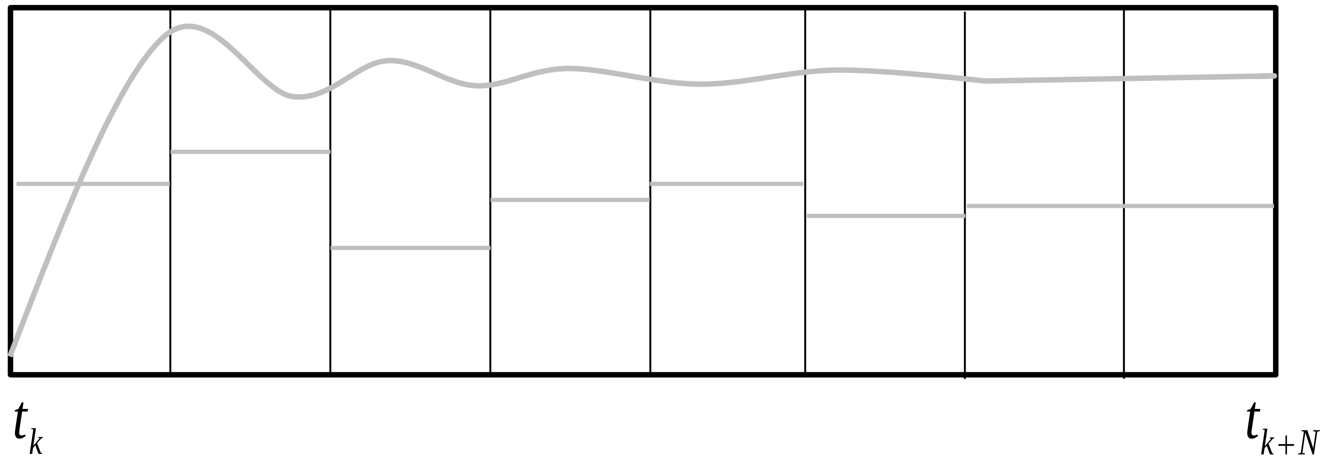
$$\min_{v} \quad \Psi(z_N) + \sum_{l=0}^{N-1} \psi(z_l, v_l)$$

$$\begin{aligned} s.t. \quad & z_{l+1} = f(z_l, v_l) \\ & c_l \le C(z_l, v_l) \le c_u \\ & z_0 = x(t_k) \end{aligned}$$

Uniform grids:

Larger optimization problem

- NMPC temporal discretization



NMPC with nonuniform grids

- NMPC formulation

$$V(x(t_k)) = \min_{v} \quad \Psi(z_N) + \sum_{l=0}^{N-1} \psi(z_l, v_l)$$

$$\begin{aligned} s.t. \quad & z_{l+1} = f(z_l, v_l), \quad l = 0, \ldots, N_0 - 1 \\ & z_{l+1} = f^{j}(z_l, v_l), \quad j = 1 \ldots n_b \\ & l = \sum_{j'=0}^{j-1} N_{j'} \ldots \sum_{j'=0}^{j} N_{j'} \\ & v = Mq \\ & c_l \le C(z_l, v_l) \le c_u, \quad z_0 = x(t_k) \end{aligned}$$

→ State blocking

→ Input blocking

Uniform grids:

Larger optimization problem

Nonuniform grids [3]:

Smaller optimization problem

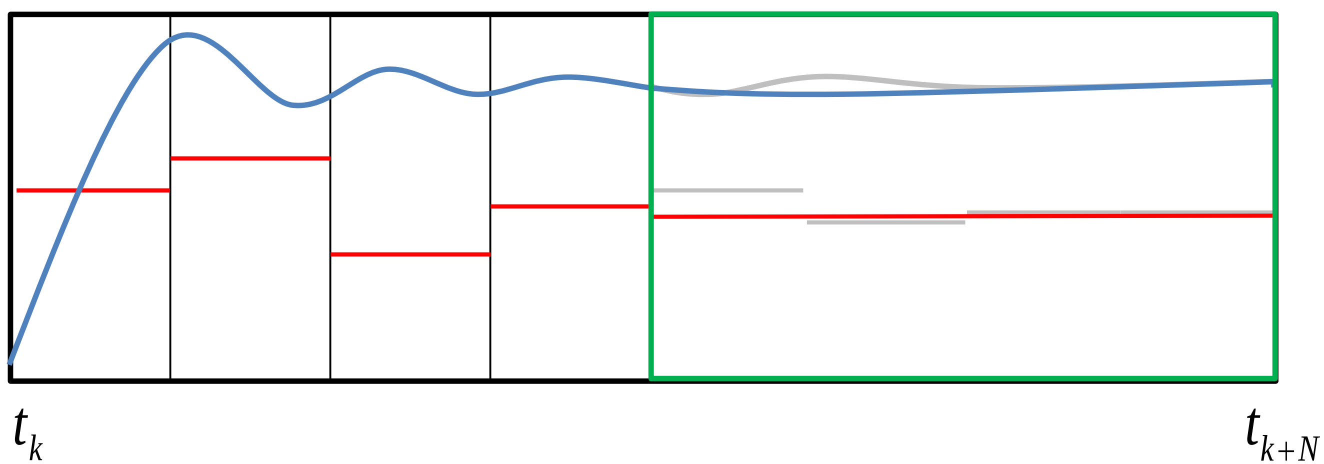
Not recursively feasible

Errors in state approximation

Stability constraint:

$$V(x(t_{k+1})) \le V(x(t_k)) - (1-\rho)\psi(x(t_k), u(t_k)) + \varepsilon_w$$

- NMPC temporal discretization



[3] Yu, M. & Biegler, L.T. A Stable and Robust NMPC Strategy with Reduced Models and Nonuniform Grids, Submitted to DYCOPS-CAB, 2016

Case study setting

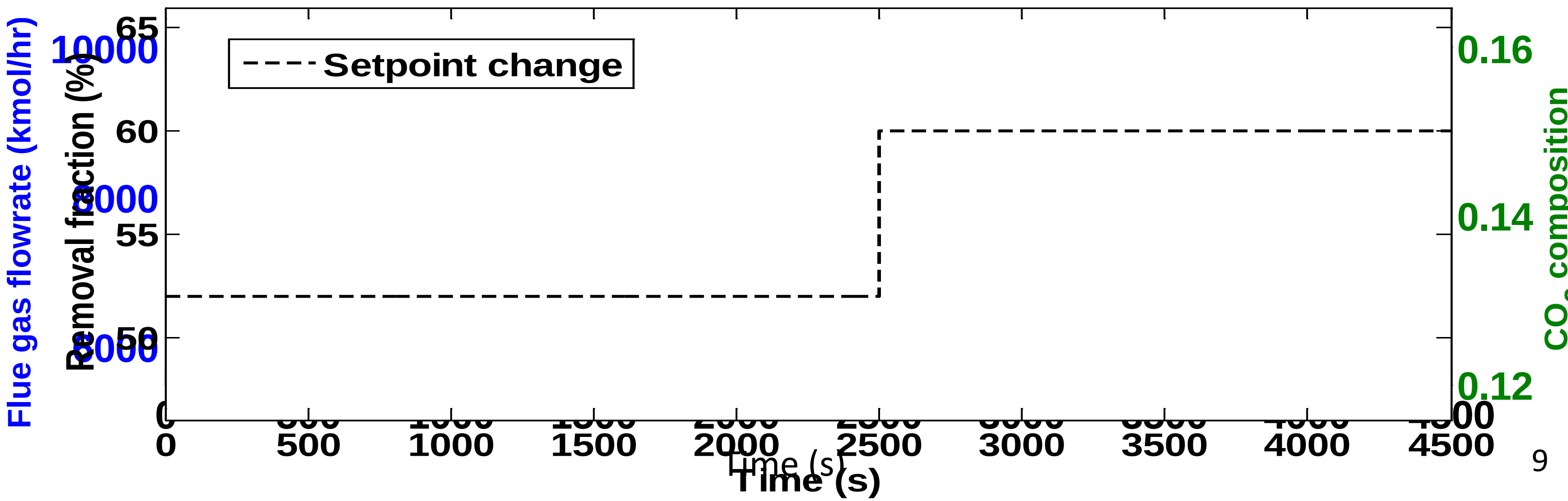
- Control case study

  Disturbances: Flowrate and composition variations in flue gas
  Controlled variable: CO_2 removal fraction
  Manipulated variable: Solid sorbent flow

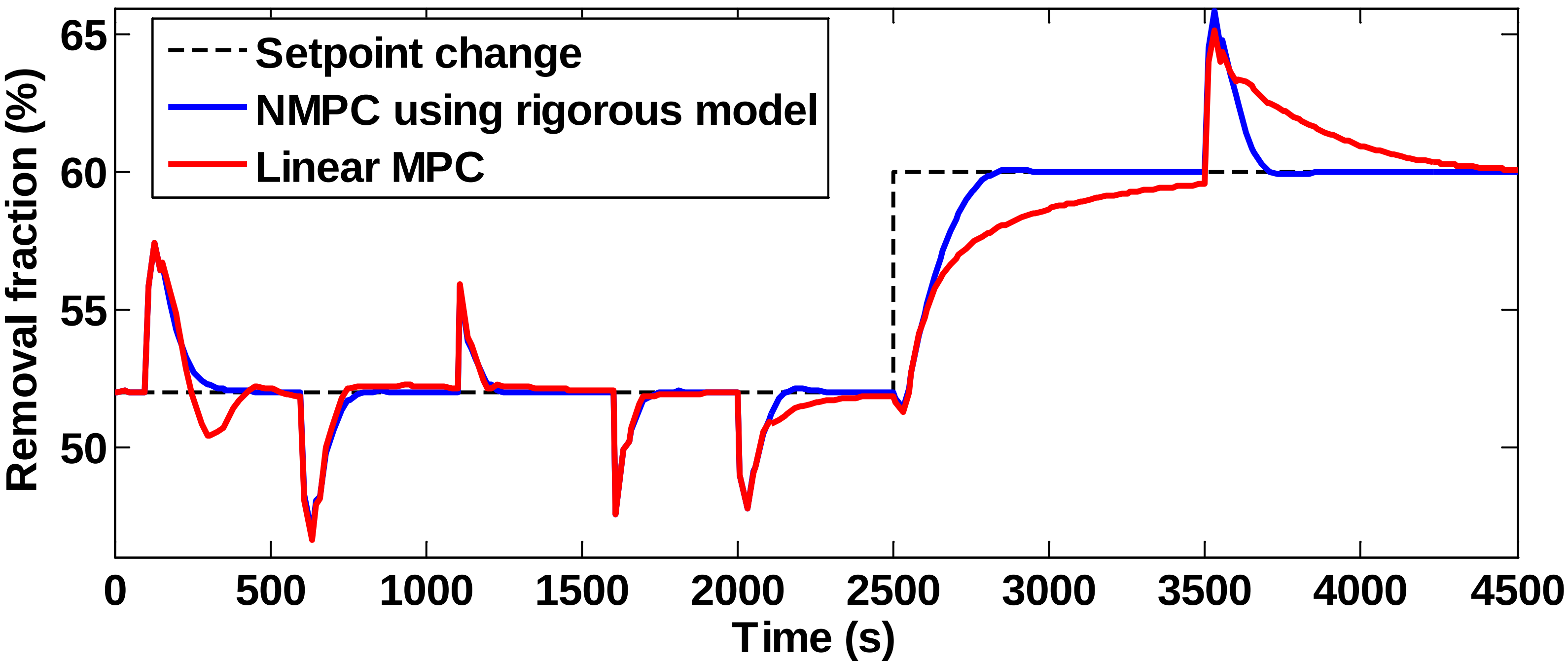
- Temporal discretization with nonuniform grids

  Prediction horizon = 400 sec
  Sampling time = 50 sec

  3 finite elements with length = 50 sec
  1 finite element with length = 250 sec



Simulation results
Comparison between nonlinear and linear MPC

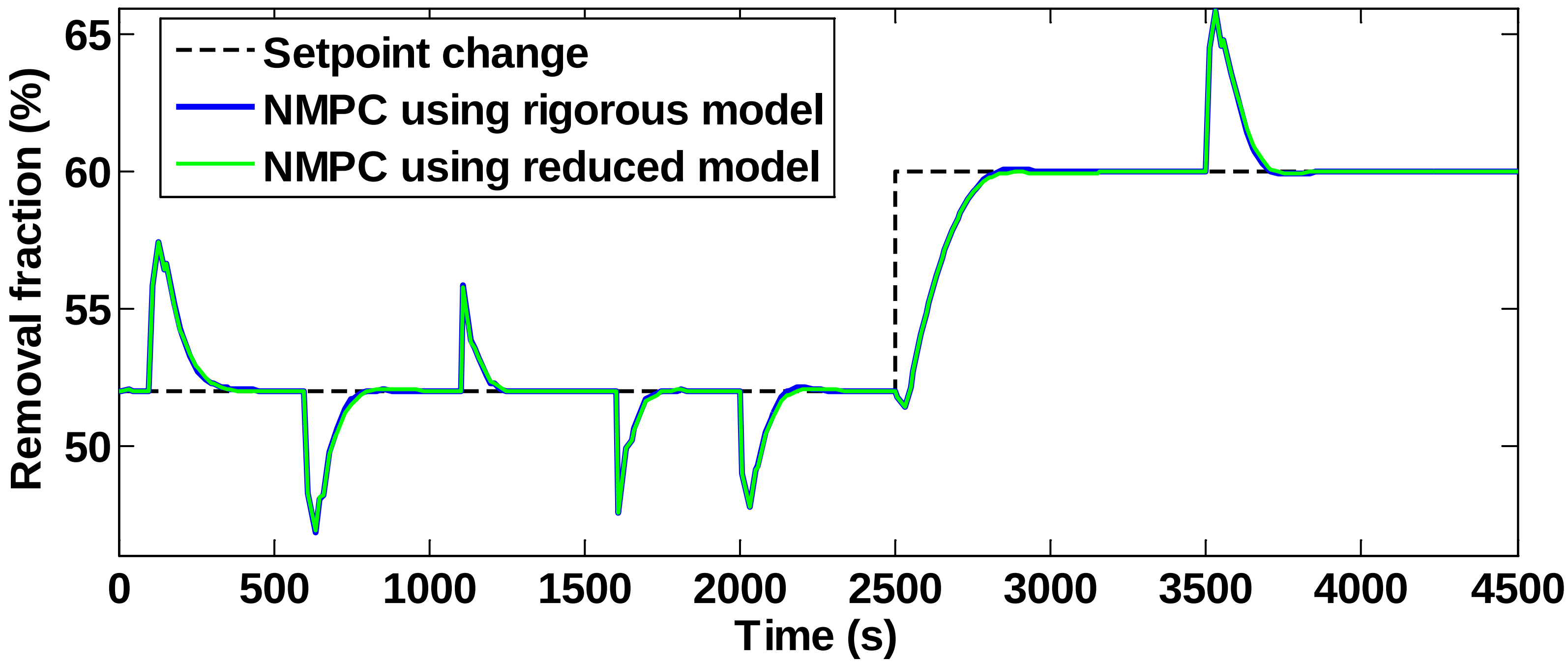


Nonlinear MPC: better tracking performance, but computationally expensive

Linear MPC: valid in small range, but computationally cheap

Simulation results

Comparison between NMPC using rigorous and reduced model

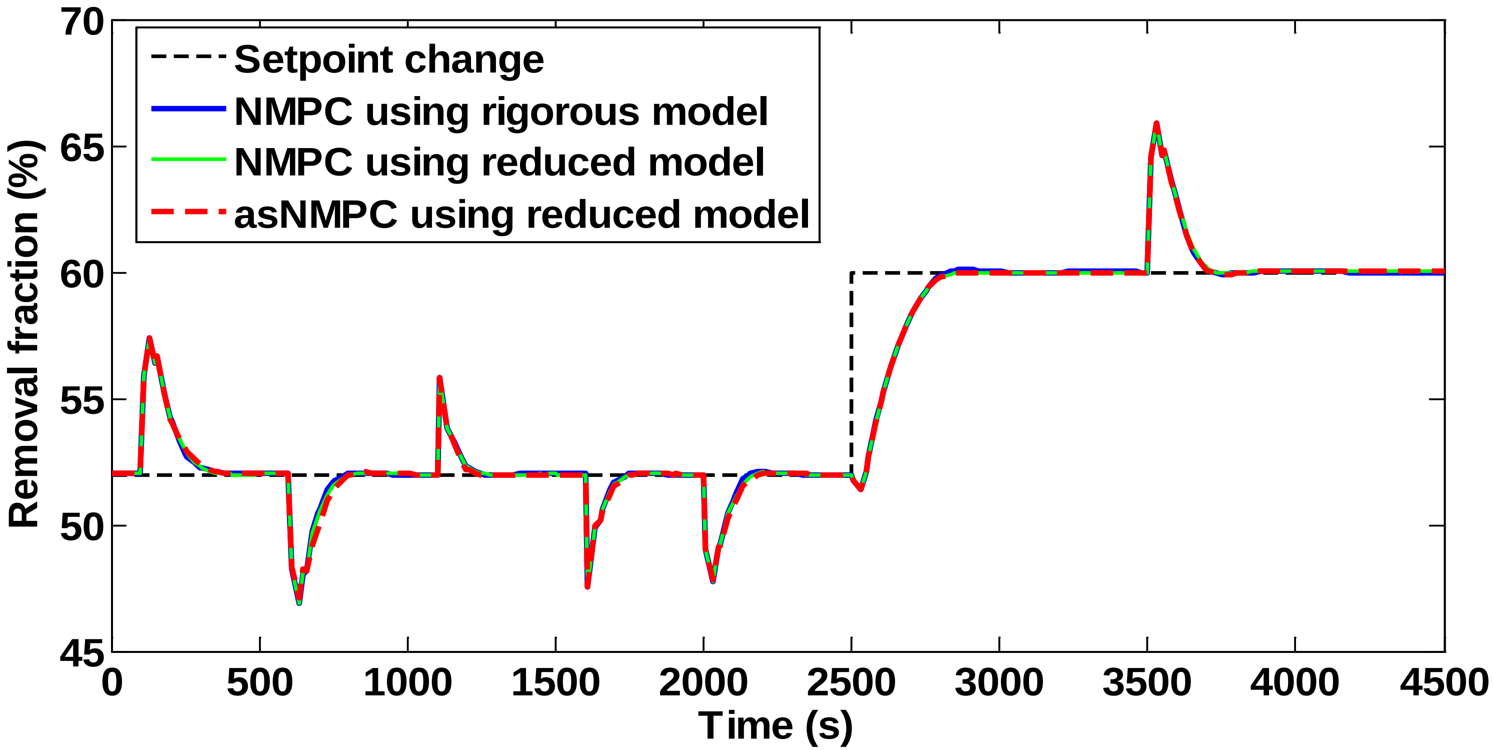


	Model size	Average time (sec)	Maximum time (sec)
NMPC w/ rigorous model	166745	56.74	256.09
NMPC w/ reduced model	64229	23.86	39.36

- Tested on an Intel i7-930 2.80 GHz PC

NMPC w/ reduced model: less than a sampling time, possible for online control

Simulation results
Advanced step NMPC using reduced model



- Advanced step NMPC [4]

Background calculation: using predicted state z(k+1) as initial condition, solve NMPC in advance to calculate control for next sampling time u(k+1)

Online update: once obtain true state x(k+1), update u(k+1) based on NLP sensitivity

Average online computational time: 1.04 sec **(**similar to Linear MPC**)**

[4] Zavala, V. M., & Biegler, L. T. (2009). The advanced-step NMPC controller: Optimality, stability and robustness. *Automatica*, *45*(1), 86-93.

Conclusions & Future work

- Conclusions
  - Developed computationally efficient and accurate dynamic reduced models for BFB adsorber using temporal and spatial model reduction methods
  - Incorporated the dynamic reduced model into NMPC and enabled online control of the BFB adsorber
  - NMPC using reduced model achieved the same control performance as rigorous model, with improved computational efficiency

- Future work
  - Integrate moving horizon estimation to improve control performance
  - Study economic NMPC problem for integrated carbon capture system

Thank you for your attention

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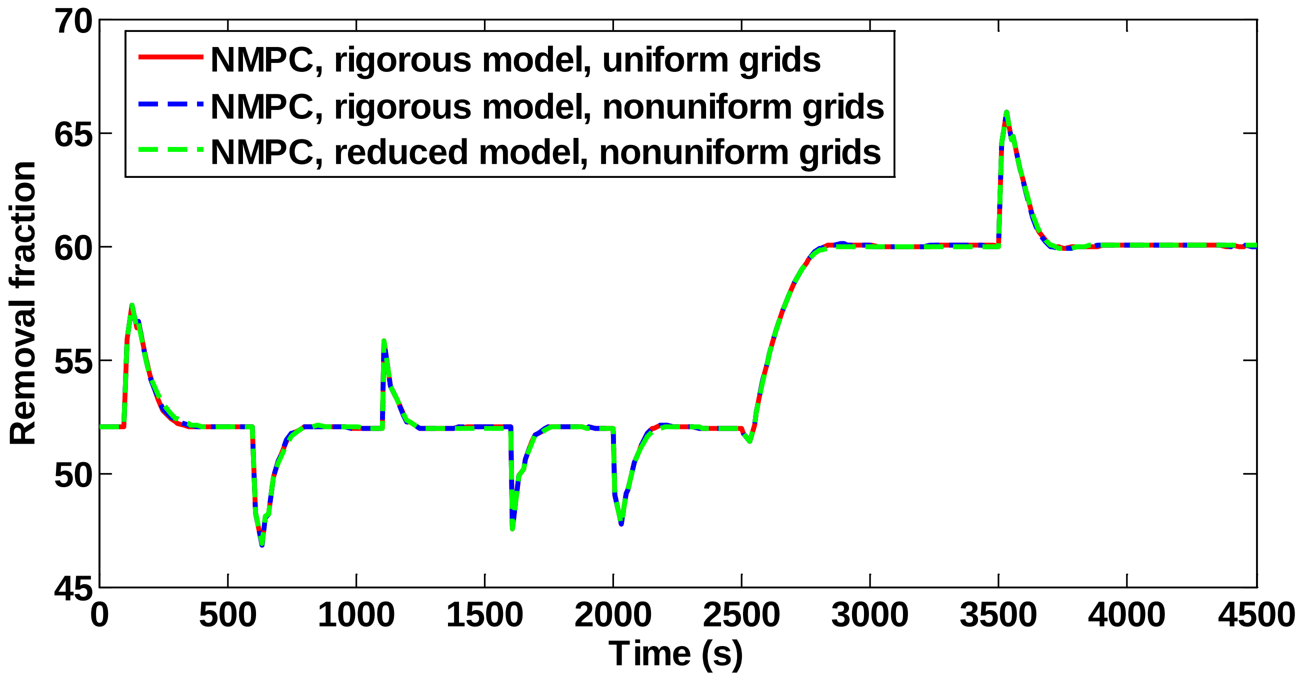
Simulation results

Comparison between NMPC w/ uniform and nonuniform grids



	Model size	Average time (sec)	Maximum time (sec)
NMPC w/uniform grids	319136	260.67	906.34
NMPC w/ rigorous model	166745	56.74	256.09
NMPC w/ reduced model	64229	23.86	39.36

- Tested on an Intel i7-930 2.80 GHz PC