Real-Time Optimization and Nonlinear Model Predictive Control for a Post-Combustion Carbon Capture Absorber

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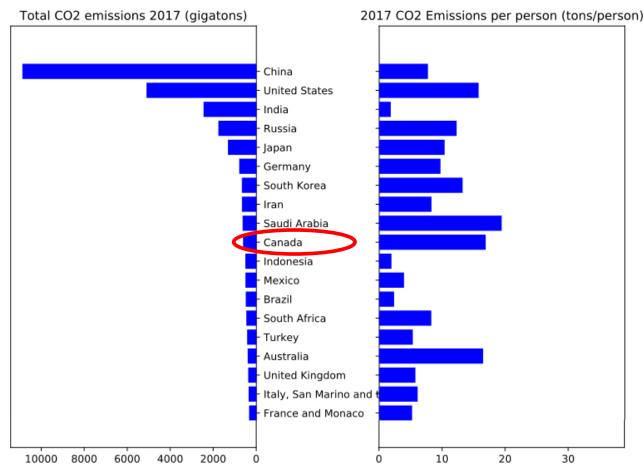


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The CO₂ problem



Muntean, M., Guizzardi, D., Schaaf, E., Crippa, M., Solazzo, E., Olivier, J. and Vignati, E. (2018). *Fossil CO2 Emissions of All World Countries: 2018 Report*. Luxembourg: Joint Research Centre (European Commission).

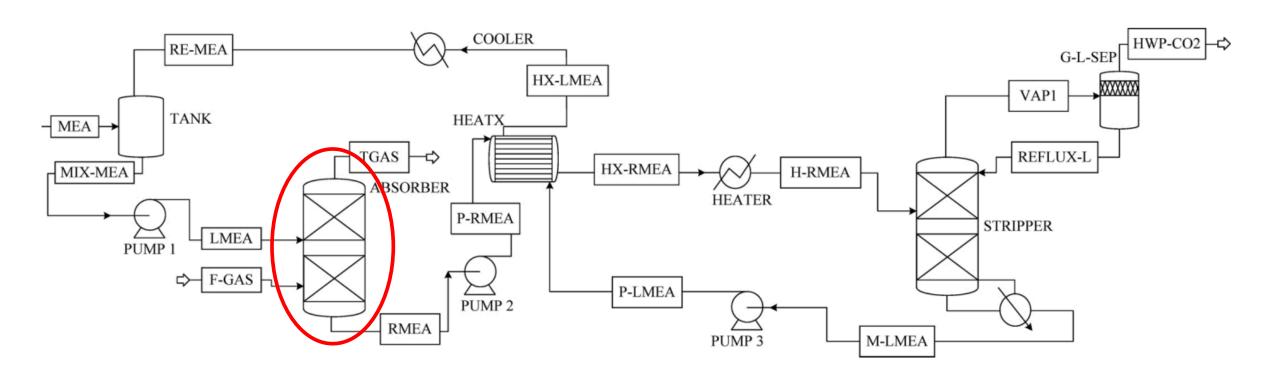
CO2 capture methods

- Pre-combustion
- Oxy-combustion
- Chemical looping combustion
- Post-combustion (PCC)*

*most mature technology



MEA Solvent Post Combustion Carbon Capture (PCC) System



L. Teck Chan and J. Chen. Economic model predictive control of an absorber-stripper CO₂ capture process for improving energy cost. IFAC-PapersOnLine, vol. 51, no. 18, pp. 109-114, 2018.



PCC economic operation and control

- Nonlinear model prediction control (NMPC)
 - Reduced order absorber model (Akeson et al.,2012)
 - Robust mechanistic absorber model (Patrón and Ricardez-Sandoval, 2020)
- Economical operation
 - Linear multivariable MPC for PCC plant (Panahi and Skogestad, 2012)
- Economic MPC
 - Chan and Chen (2018)
 - Decardi-Nelson, Liu and Liu (2018)

A two-layer RTO approach has not been tested for the PCC



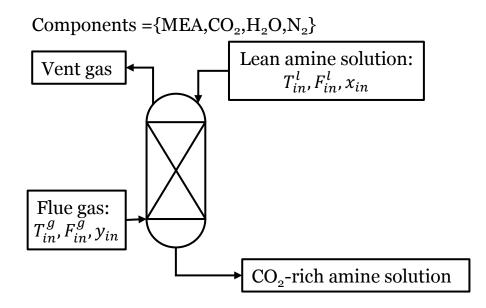
Motivation, Challenges, and Objectives

Motivation

- The absorber is of economic detriment to the upstream power plant
- The power plant introduces disturbances to the absorber, creating economic suboptimality

<u>Objectives</u>

 Operate the absorber in an economically optimal way subject to upstream disturbances and changing carbon tax prices



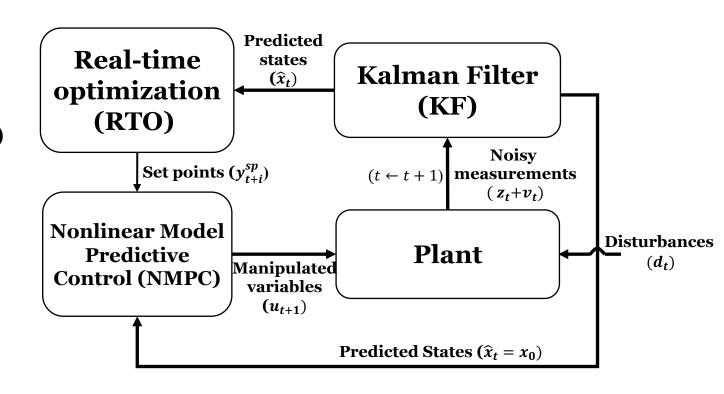
<u>Challenges</u>

- Cost reduction and carbon capture are conflicting objectives
- State estimation is required



Research objectives

- Novel RTO formulation for absorber
- Mechanistic process model in RTO and NMPC layer
- State estimation for absorber



*all methods require models



Differential Model of CO_2 Absorber Column - f(x)

 $i=MEA,CO_2,H_2O,N_2$

* Adapted from Harun et al. (2012)

	Mass
Liquid	$\frac{dC_i^l}{dt} = u_l \frac{\partial C_i^l}{\partial z} + a_w N_i$
Gas	$\frac{dC_i^g}{dt} = -u_g \frac{\partial C_i^g}{\partial z} - a_w N_i - C_i^g \frac{\partial u_g}{\partial z}$
	Energy
Liquid	$\frac{dT_{l}}{dt} = u_{l} \frac{\partial T_{l}}{\partial z} - \frac{a_{w}}{\sum_{i=1}^{4} c_{p,i}^{l} C_{i}^{l}} \left[h_{gl} \left(T_{l} - T_{g} \right) + \Delta H_{rxn} N_{CO_{2}} - \Delta H_{H_{2}O}^{vap} N_{H_{2}O} + h_{out} \left(T_{l} - T_{amb} \right) \right]$
Gas	$\frac{dT_g}{dt} = -u_g \frac{\partial T_g}{\partial z} + \frac{a_w}{\sum_{i=1}^4 c_{p,i}^g C_i^g} \left[h_{gl} \left(T_l - T_g \right) \right]$

- Phenomenological and physical property equations (h(x))
- Non-discretized model has 12 PDEs and 160 AEs



Model Implementation

- PDAEs discretized by finite differences in axial domain and orthogonal collocations in time domain
- Model size (after discretization):
 - Axially (RTO) \Rightarrow ~2,000 nonlinear algebraic equations
 - Axially and temporally (NMPC) $\Rightarrow \sim 64,000$ nonlinear algebraic equations
- IPOPT (Wächter and Biegler, 2005)

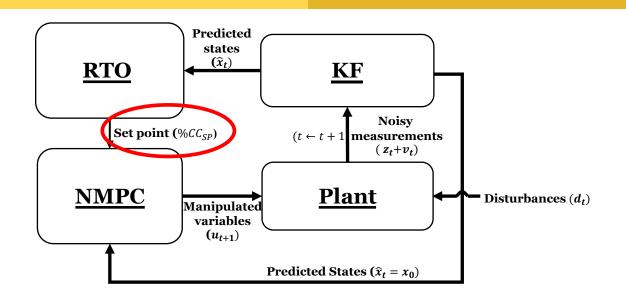




RTO Formulation

- Steady-state optimization
- Three sources of cost:
 - MEA degradation (per tonne of CO₂ removed)
 - Carbon Tax (per tonne of CO₂ emitted)
 - Electricity

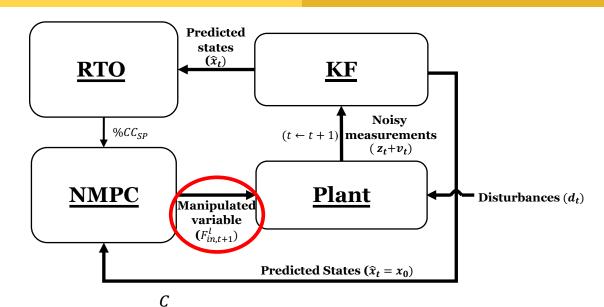
$$\begin{aligned} & \min_{\%CC_{SP}} P_{\text{MEA}} \dot{m}_{\text{CO}_2,out}^l + P_{\text{CO}_2} \dot{m}_{\text{CO}_2,out}^g + P_{\text{e}} W_{\text{pump}} \\ & s. t. \\ & f(x_t, u_t) = \mathbf{0} \\ & h(x_t, u_t) = \widehat{Y}_t \\ & u^l \leq u_t \leq u^h \end{aligned}$$





NMPC Formulation

- Dynamic optimization
- Tracking and move suppression terms
- Manipulated variable bounds



$$\min_{\substack{F_{in,t+j}^{g} \forall j \in \{1,...,C\}\\ F_{in,t+j}^{g} \forall j \in \{1,...,C\}}} \mathbf{Q} \sum_{i=1}^{P} (\widehat{\mathscr{C}C}_{t+i} - \mathscr{C}C_{SP})^{2} + \mathbf{R} \sum_{j=1}^{C} \Delta F_{in,t+j}^{l}^{2}$$
s. t.
$$f(\mathbf{x}_{t}, \mathbf{u}_{t+j}) = \widehat{\mathbf{x}}_{t+i}; \qquad \forall i \in \{1, ..., P\} \\
\forall j \in \{1, ..., C\}$$

$$\mathbf{x}_{t} = \mathbf{x}_{0}$$

$$\mathbf{h}(\widehat{\mathbf{x}}_{t+i}, \mathbf{u}_{t+j}) = \widehat{\mathbf{Y}}_{t+i}; \qquad \forall i \in \{1, ..., P\}$$

$$\forall j \in \{1, ..., C\}$$

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KF Formulation

- 74/110 states measured
 - Temperatures, gas concentrations, inlet/outlet states
- *A priori* predictions generated using mechanistic model
- Jacobian matrix for generated symbolically

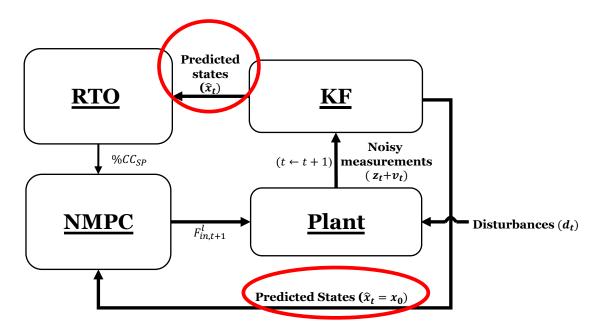
$$\bullet \widehat{x}_{k|k-1} = f(\widehat{x}_{k-1|k-1}, u_k)$$

•
$$P_{k|k-1} = J_f P_{k-1|k-1} J_f^T + Q_k$$

•
$$K_k = P_{k|k-1} J_h^T (J_h P_{k|k-1} J_h^T + R_k)^{-1}$$

$$\bullet \widehat{x}_{k|k} = \widehat{x}_{k|k-1} + K_k(z_k - H_k \widehat{x}_{k|k-1})$$

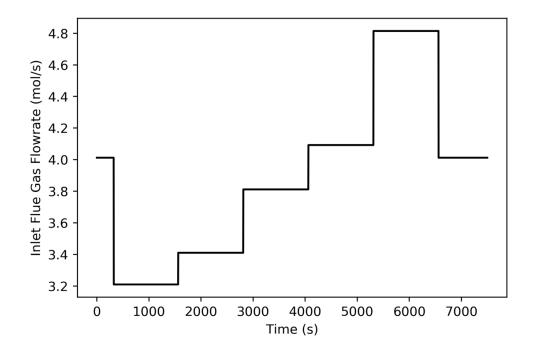
$$P_{k|k} = (I - K_k J_h) P_{k|k-1}$$

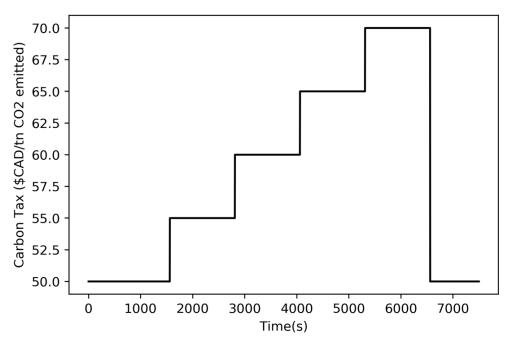




Results (test scenarios)

- 1. NMPC only (no RTO)
- 2. RTO (carbon tax at fixed 50 \$CAD/tn CO₂ emitted)
- 3. RTO (time-varying carbon tax)







Result (process cost)

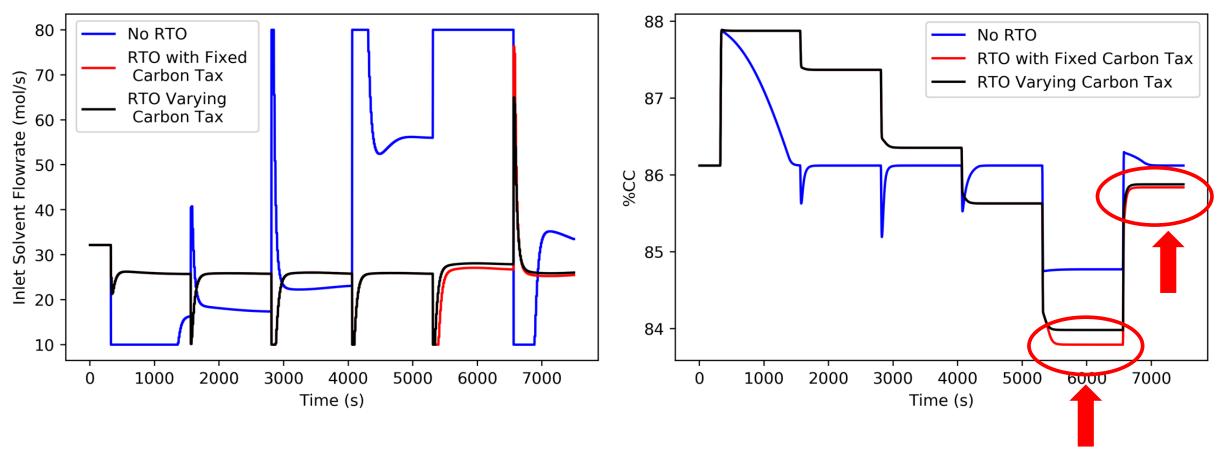
*costs in \$CAD

Scenario	Total Cost	Tax Cost	MEA Cost	Electrical Cost
No RTO (fixed tax)	13.46	6.31	7.13	0.01
No RTO (varying tax)	14.64	7.50	7.13	0.01
RTO (fixed tax)	11.98	6.31	5.67	0.01
RTO (varying tax)	13.23	7.51	5.70	0.01

RTO sensitive to MEA cost



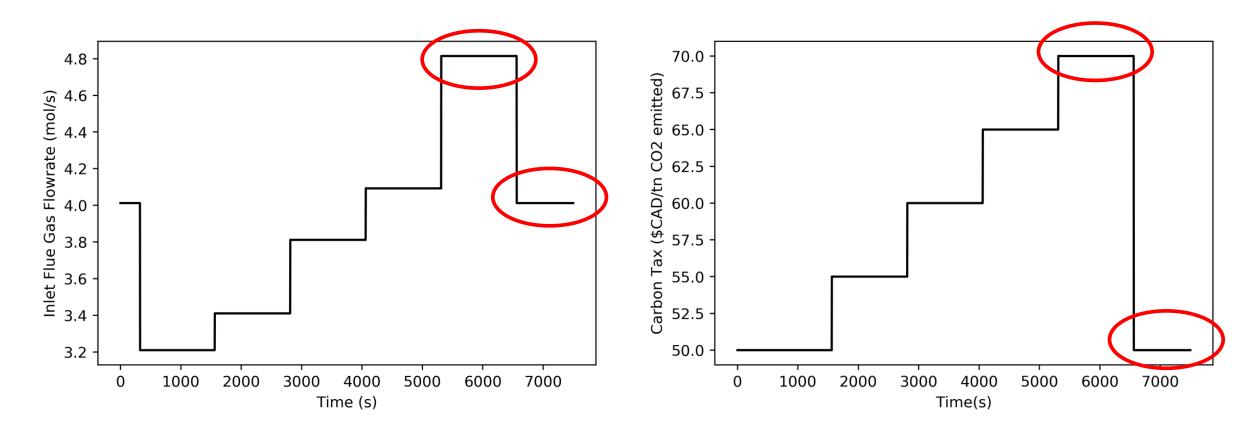
Results (profiles)



Fixed and varying tax case are only substantially different in final two RTO periods



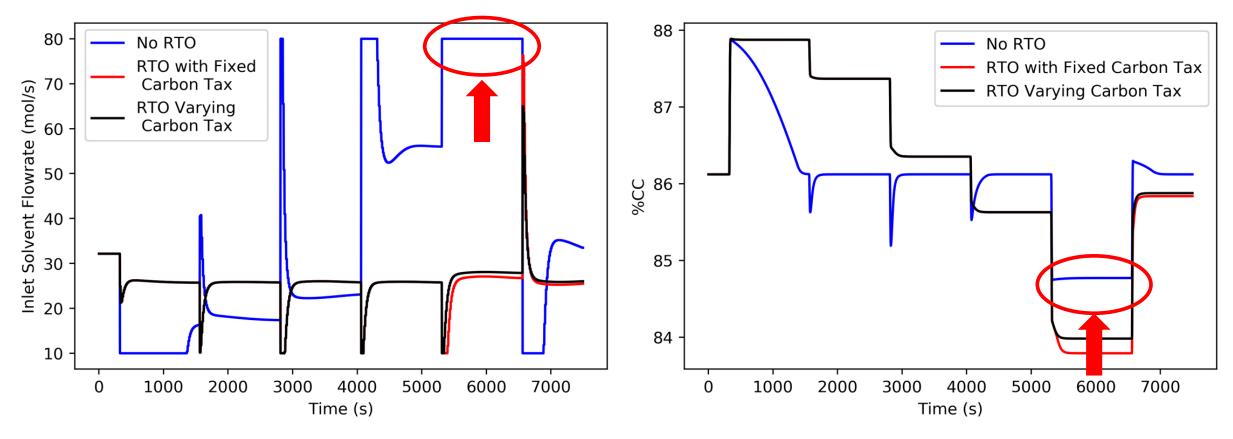
Results (profiles)



• RTO only sensitive to tax rate when it coincides with large disturbances



Results (profiles)

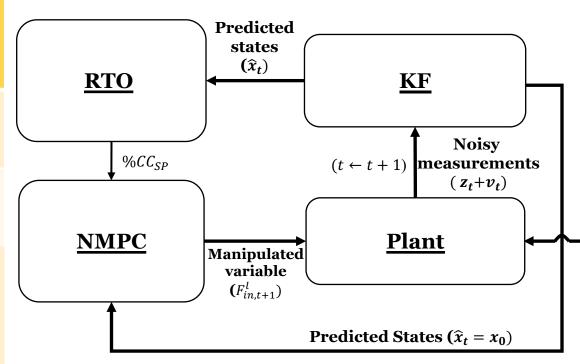


- Large disturbances cause unreachable set points in no RTO scenario
- These are avoided by the executing the RTO



Results (computational times)

	CPU time [s]	Number of equations	Key outputs
RTO	~15 s	1,861	$1 \\ (\%CC_{SP})$
NMPC	~60 s	64,480	$9\left(F_{in,t+1}^{l}\right)$
KF (a priori)	~4 s	1,861	110 (2)
KF (a posteriori)	<1 S	110	110 (\hat{x}_t)





Conclusions

- RTO provides substantial economic benefit and avoids unreachable setpoints
- Carbon tax rate only impacts economics when under large disturbances
- KF is able to compute states at a computational cost

Future Work

- Investigate more advanced estimation schemes (i.e. moving horizon estimation)
- Account for plant—model mismatch via parameter or modifier adaptation
- Merge RTO and NMPC layers by formulating an economic NMPC
- Consider entire post-combustion CO2 plant (i.e. stripper, heat exchange units, tanks)



Thank you

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https://uwaterloo.ca/chemical-process-optimization-multiscale-modelling-process-systems/



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