

FOQUS: A Framework for Optimization and Quantification of Uncertainty

Extending the Capabilities of Aspen Plus and Aspen Custom Modeler

David C. Miller,^{a*} John Eslick,^c Josh Boverhof,^d Jim Leek,^b Charles Tong,^b Yang Chen,^c Brenda Ng,^b Jeremy Ou,^b Nikolaos V. Sahinidis^c

^aNational Energy Technology Laboratory, Pittsburgh, PA USA
^bLawrence Livermore National Laboratory, Livermore, CA USA
^cCarnegie Mellon University, Dept of Chemical Engineering, Pittsburgh, PA USA
^dLawrence Berkeley National Laboratory, Berkeley, CA USA



CCSI For Accelerating Technology Development





Rapidly synthesize optimized processes to identify promising <u>concepts</u>



Better understand internal behavior to reduce time for troubleshooting





larger scales faster



Stabilize the cost during commercial deployment



Goals & Objectives of CCSI

- <u>Develop</u> new computational tools and models to enable industry to more rapidly develop and deploy new advanced energy technologies
 - Base development on industry needs/constraints
- <u>Demonstrate</u> the capabilities of the CCSI Toolset on nonproprietary case studies
 - Examples of how new capabilities improve ability to develop capture technology
- Deploy the CCSI Toolset to industry
 - Initial licensees



Tools to develop an optimized process using rigorous models



Framework for Optimization, Quantification of Uncertainty and Sensitivity



D. C. Miller, B. Ng, J. C. Eslick, C. Tong and Y. Chen, 2014, Advanced Computational Tools for Optimization and Uncertainty Quantification of Carbon Capture Processes. In Proceedings of the 8th Foundations of Computer Aided Process Design Conference – FOCAPD 2014. M. R. Eden, J. D. Siirola and G. P. Towler Elsevier.









Carbon Capture System Configuration



- Discrete decisions: How many units? Parallel trains? What technology used for each reactor?
- Continuous decisions: Unit geometries
- Operating conditions: Vessel temperature and pressure, flow rates, compositions



ALAMO: Model Development & Overfitting

Step 1: Define a large set of potential basis functions





Adaptive Sampling Improves Surrogate Model

- We use an iterative design of experiments to
 - Sample better or sample fewer data points
- Two models given the same data set size:



Carbon Capture Reactors



Superstructure Optimization

Mixed-integer nonlinear programming model in GAMS

- Parameters
- Variables
- Equations
 - Economic modules
 - Process modules
 - Material balances
 - Hydrodynamic/Energy balances
 - Reactor surrogate models
 - Link between economic modules and process modules
 - Binary variable constraints
 - Bounds for variables



Optimal layout







Simulation-Based Optimization and Simultaneous Heat Integration





FOQUS Flowsheet



13

FOQUS Problem Definition

Decision Variables

Objective

Constraints

sior	Flowsheet	Uncertain) ty	Optimiz	ation Su	y=f(x) rrogates	Relp		
oble Dec	em Solver F	Run							
	Variable	2	Sc	ale	Min	Max	Value		
1	BFB.adsDt	L	.inea	r 🔻	9.0	15.0	10.858557456482906	=	
2	BFB.adsdx		Linear 🔻		0.0175	0.03	0.0175		
3	BFB.adslhx		Linear 🔻		0.0075	0.55	0.17531815351899785		
4	BFB.adsN		Linear 🔻		4.0	15.0	11.275189518249599	-	
Obj	ective Function f(x))			1				
Expression Penalty Sca			ale Value for Failur			re		+	
1	f["Cost"]["COE"]	1.0	800.0					-	
Ine	quality Constraints	g(x) <= 0					,		
	Expression Penalty F				actor	Form		+	
1	1 0.9-f["BFB"]["removalCO2"] 1000.0						•	-	
		√ 0	heck	Input.) 🔍 v	ariable Exp	lorer		















Objective Function: Maximize **Net efficiency**

Constraint: **CO**₂ **removal** ratio \ge 90% Flowsheet evaluation (via process simulators) Minimum utility target (via heat integration tool)

Decision Variables (17): Bed length, diameter, sorbent and steam feed rate



Optimization with Heat Integration

	w/o heat integration	Sequential	Simultaneous
Net power efficiency (%)	31.0	32.7	35.7
Net power output (MW_e)	479.7	505.4	552.4
Electricity consumption b (MW _e)	67.0	67.0	80.4
IP steam withdrawn from power cycle (MW $_{\rm th}$)	0	0	0
LP steam withdrawn from power cycle (MW _{th})	336.3	304.5	138.3
Cooling water consumption ^b (MW _{th})	886.8	429.3	445.1
Heat addition to feed water (MW_{th})	0	125.3	164.9

Base case w/o CCS: 650 MW $_{\rm e}$, 42.1 %









Uncertainty Quantification for Prediction Confidence

- Now that we have
 - A chemical kinetics model with quantified uncertainty
 - A process model with other sources of uncertainty
 - Surrogates with approximation errors
 - An optimized process based on the above
- UQ questions
 - How do these errors and uncertainties affect our prediction confidence (e.g. operating cost) for the optimized process?
 - Can the optimized system maintain >= 90% CO2 capture in the presence of these uncertainties?
 - Which sources of uncertainty have the most impact on our prediction uncertainty?
 - What additional experiments need to be performed to give acceptable uncertainty bounds?



Set up uncertain parameters













19

Generate simulation ensembles with FOQUS



Perform statistical analyses with FOQUS



🏠 🔾 🔾 🕂 🧭 👼 😿 Error mean: 0.000627 Error std dev: 3.989587 RS validation 200 250 300 Actual Data for Cost coe obi

Ensemble Analyses

- > Uncertainty analysis
- Sensitivity analysis
- ➤ Correlation analysis
- Scatterplots for visualization

Response Surface (RS) Analyses

- ➢ RS validation
- ➢ RS visualization
- ➢ RS-based uncertainty analysis
- ➢ RS-based sensitivity analysis
- RS-based Bayesian inference









NET Carbon Canture Simulation Initiativ







EST 1943

UQ in Solvent System Models



Framework for Optimization, Quantification of Uncertainty and Sensitivity



D. C. Miller, B. Ng, J. C. Eslick, C. Tong and Y. Chen, 2014, Advanced Computational Tools for Optimization and Uncertainty Quantification of Carbon Capture Processes. In *Proceedings of the 8th Foundations of Computer Aided Process Design Conference – FOCAPD 2014.* M. R. Eden, J. D. Siirola and G. P. Towler Elsevier.



Acknowledgements

- SorbentFit
 - David Mebane (NETL/ORISE, West Virginia University)
 - Joel Kress (LANL)
- Process Models
 - Debangsu Bhattacharyva, Srinivasarao Modekurti, Ben Omell (West Virginia University)
 - Andrew Lee, Hosoo Kim, Juan Morinelly (NETL/ORISE)
- FOQUS
 - ALAMO: Nick Sahinidis, Alison Cozad, Zach Wilson (Carnegie Mellon University)
 - Superstructure: Nick Sahinidis, Zhihong Yuan (Carnegie Mellon University)
 - DFO: John Eslick (NETL/ORISE, Carnegie Mellon University), Qianwen Gao (NETL/ORISE)
 - Heat Integration: Yang Chen, Ignacio Grossmann (Carnegie Mellon University)
 - UQ: Charles Tong, Brenda Ng, Jeremey Ou
 - Turbine: Josh Boverhof, Deb Agarwal (LBNL)
 - SimSinter: Jim Leek (LLNL), John Eslick (NETL/ORISE, CMU)
- Data Management
 - Tom Epperly (LLNL)
 - Deb Agarwal, You-Wei Cheah (LBNL)

Disclaimer This presentation was prepared as an account of work sponsored by an agency of the United States Government. Neither the United States Government nor any agency thereof, nor any of their employees, makes any warranty, express or implied, or assumes any legal liability or responsibility for the accuracy, completeness, or usefulness of any information, apparatus, product, or process disclosed, or represents that its use would not infringe privately owned rights. Reference herein to any specific commercial product, process, or service by trade name, trademark, manufacturer, or otherwise does not necessarily constitute or imply its endorsement, recommendation, or favoring by the United States Government or any agency thereof. The views and opinions of authors expressed herein do not necessarily state or reflect those of the United States Government or any agency thereof.

