

**CCSI**<sup>TM</sup>  
Carbon Capture Simulation Initiative

## **US Department of Energy's Carbon Capture Simulation Initiative: Computational Tools for Accelerating Process Development**

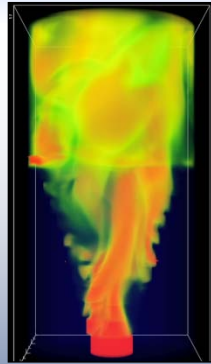
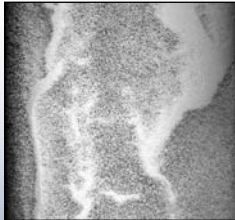
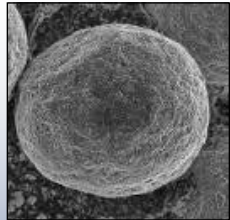
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Department of Chemical Engineering  
West Virginia University  
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U.S. Department of Energy  
National Energy Technology Laboratory  
Technical Lead, CCSI



# CCSI For Accelerating Technology Development

Carbon Capture Simulation Initiative



Identify promising concepts



Reduce the time for design & troubleshooting



Quantify the technical risk, to enable reaching larger scales, earlier



Stabilize the cost during commercial deployment

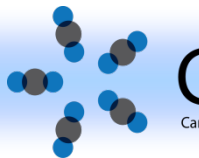
## National Labs



## Academia



## Industry

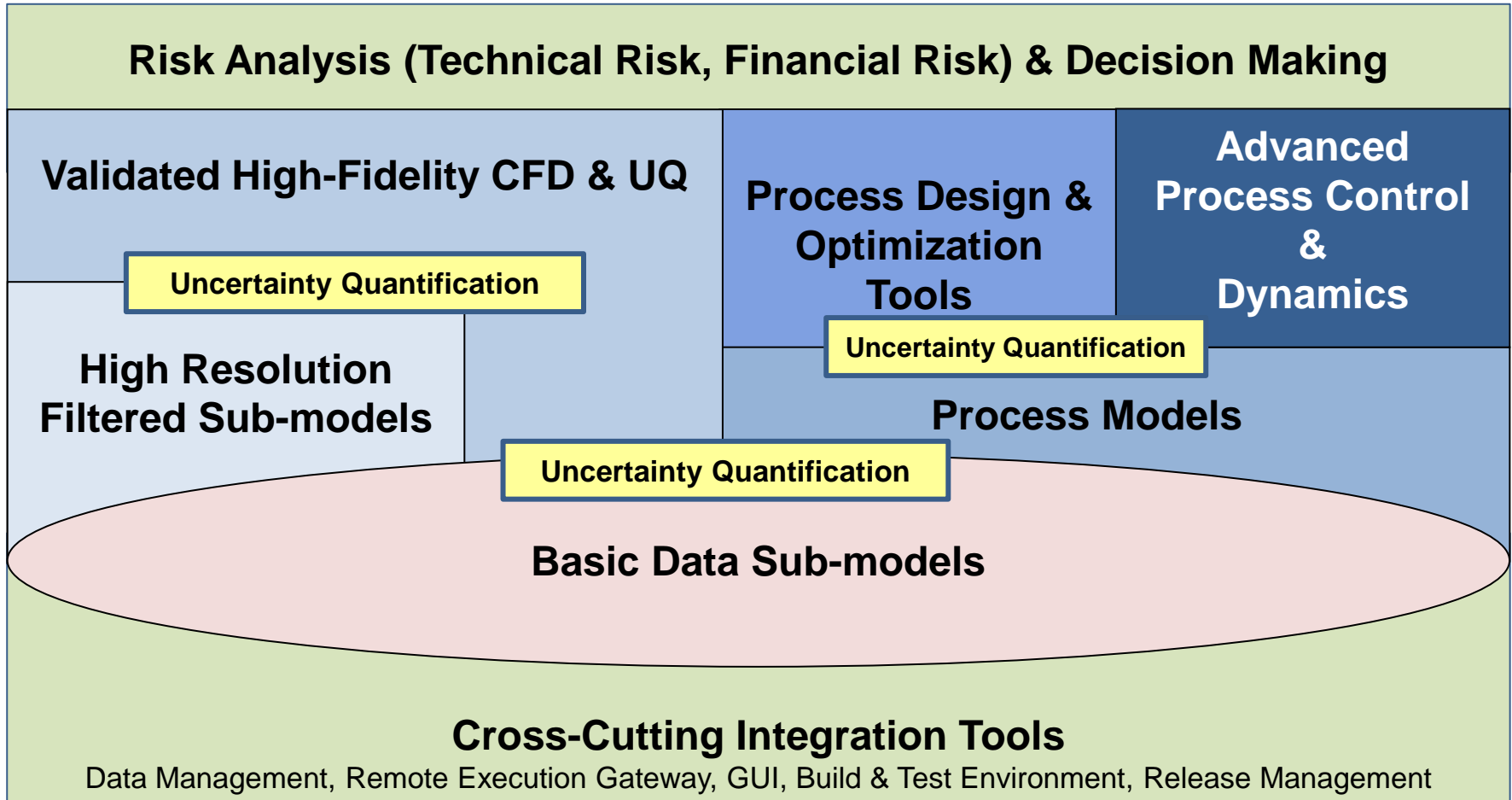


CCSI<sup>TM</sup>  
Carbon Capture Simulation Initiative

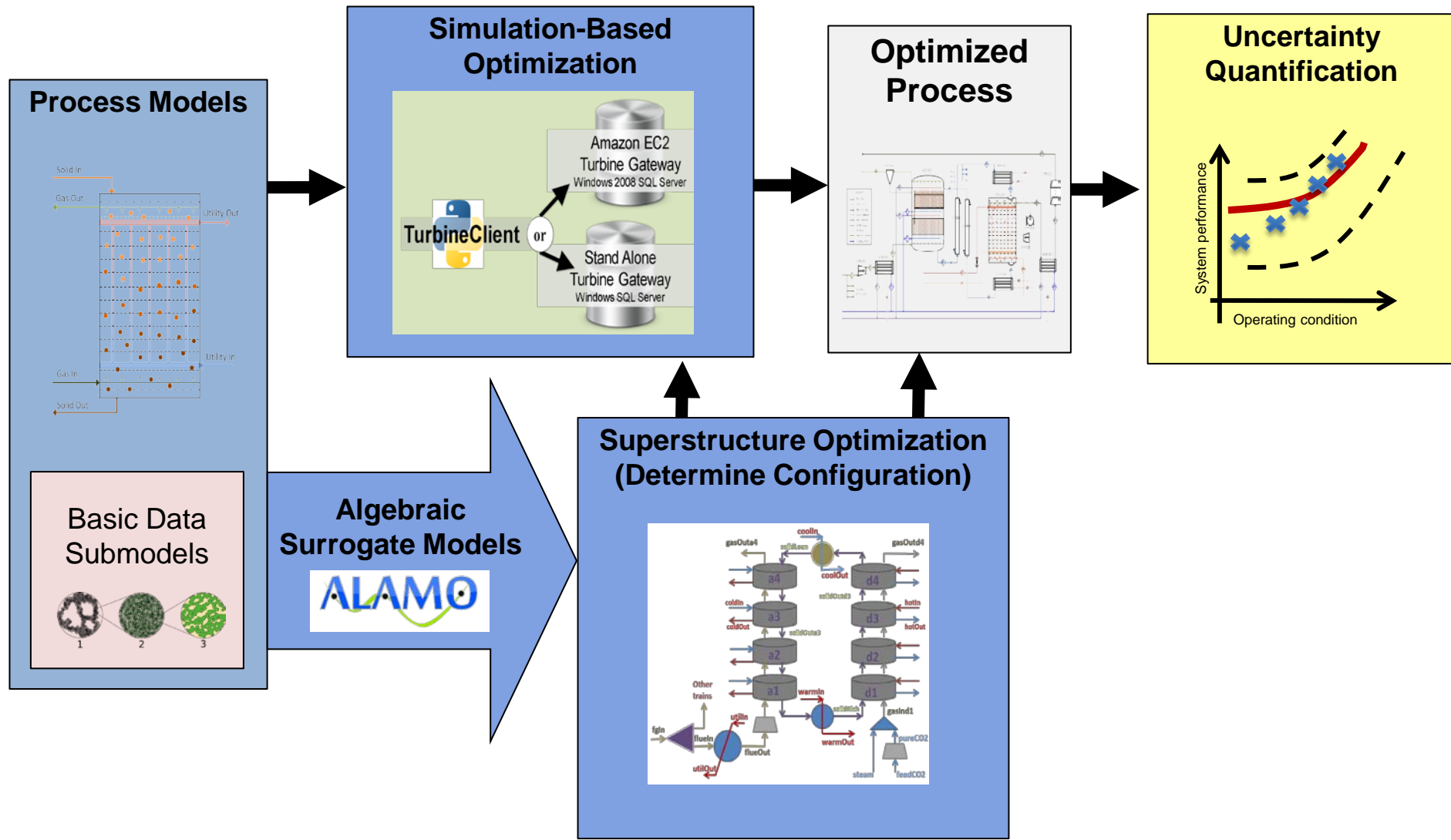


U.S. DEPARTMENT OF ENERGY  
**ENERGY**

# Advanced Computational Tools to Accelerate Next Generation Technology Development

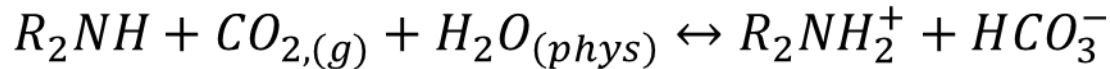
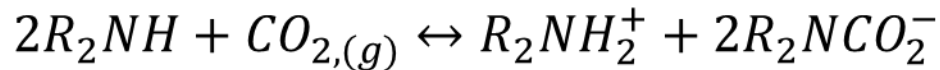
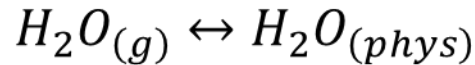
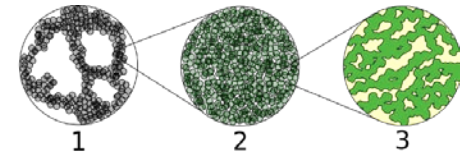


# Tools to develop an optimized process using rigorous models



# Basic Data Submodel

SORBENTFIT



$$r_{1,r,i} = k_{1,r,i} \left( \frac{P_i C_{r,H_2O,i}}{C_{r,t,i}} - \frac{n_{r,H_2O,i}}{K_{1,r,i}} \right)$$

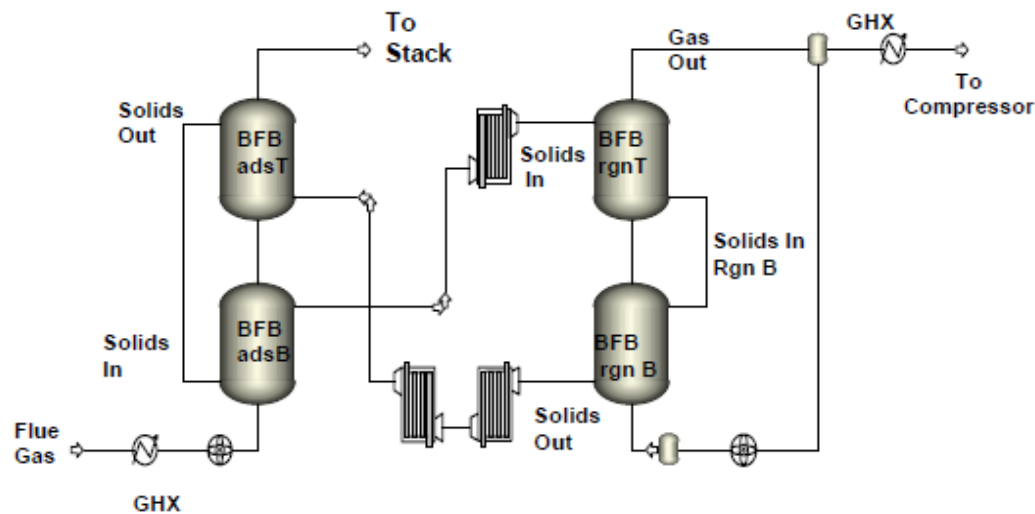
$$r_{2,r,i} = k_{2,r,i} \left( \left[ 1 - 2 \frac{n_{r,carb,i}}{n_v} - \frac{n_{r,bicarb,i}}{n_v} \right] n_{r,H_2O,i} \left[ \frac{P_i C_{r,CO_2,i}}{C_{r,t,i}} \right] - \frac{\left\{ \frac{n_{r,carb,i}}{n_v} + \frac{n_{r,bicarb,i}}{n_v} \right\} n_{r,bicarb,i}}{K_{2,r,i}} \right)$$

$$r_{3,r,i} = k_{3,r,i} \left( \left[ 1 - 2 \frac{n_{r,carb,i}}{n_v} - \frac{n_{r,bicarb,i}}{n_v} \right]^2 \left[ \frac{P_i C_{r,CO_2,i}}{C_{r,t,i}} \right] - \frac{\left\{ \frac{n_{r,carb,i}}{n_v} + \frac{n_{r,bicarb,i}}{n_v} \right\} n_{r,carb,i}}{K_{3,r,i}} \right)$$

\*Lee et al. A model for the Adsorption Kinetics of CO<sub>2</sub> on Amine-Impregnated Mesoporous Sorbents in the Presence of Water, 28<sup>th</sup> International Pittsburgh Coal Conference 2011, Pittsburgh, PA, USA.

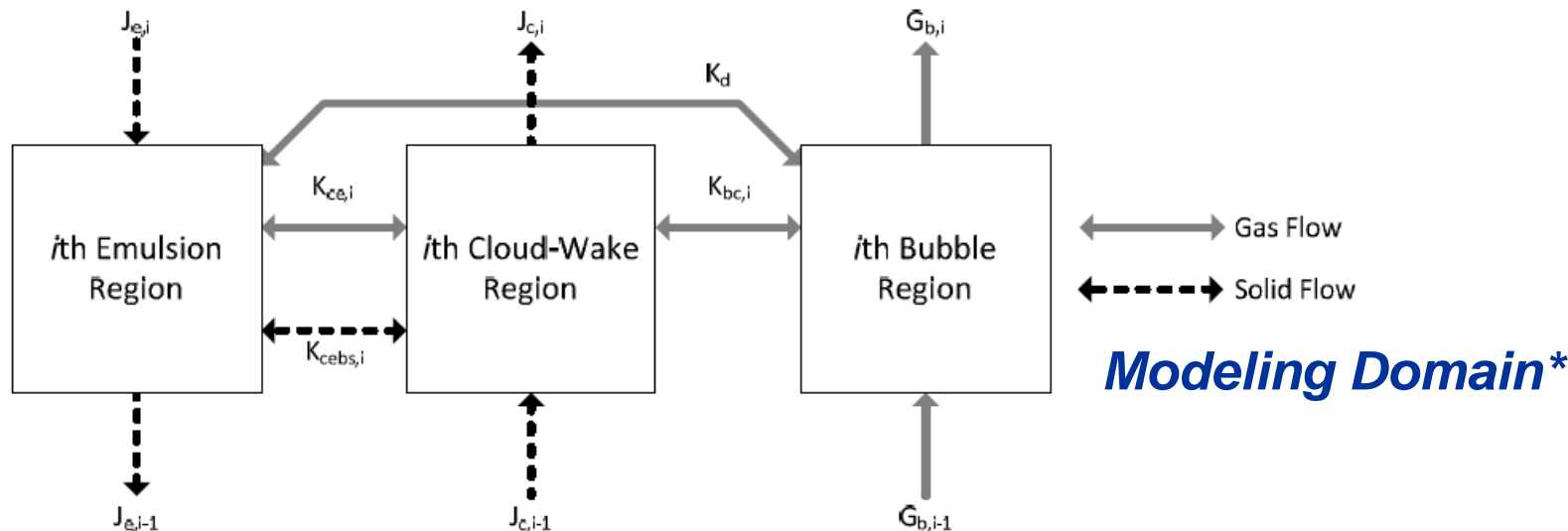
# Development of Bubbling Fluidized Bed Model

- 1-D two-phase pressure-driven non-isothermal dynamic model of a solid-sorbent CO<sub>2</sub> capture in a two-stage bubbling fluidized bed reactor system.
- Models are flexible such that it can be used as an adsorber or regenerator
- Embedded cooler/heater depending on the application
- Flexible configuration- solids can enter/leave at/from the top or bottom
- A 2-stage adsorption model with customized variables suitable for incorporating UQ has been developed





# MODEL DEVELOPMENT

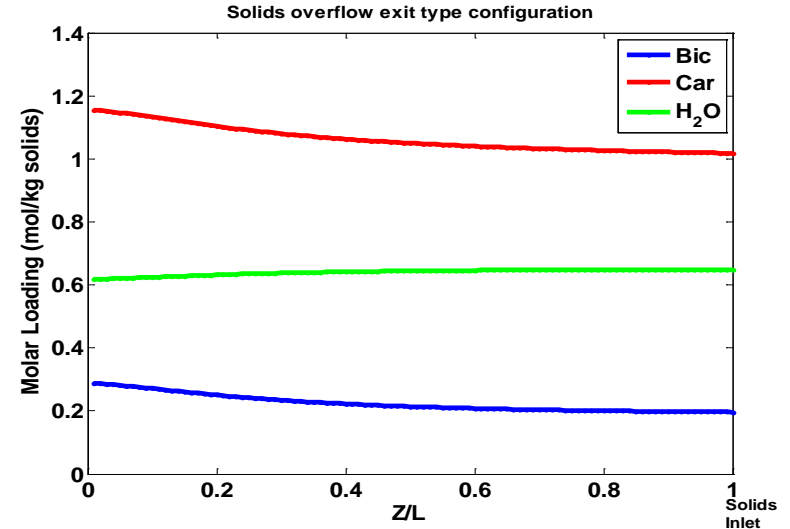
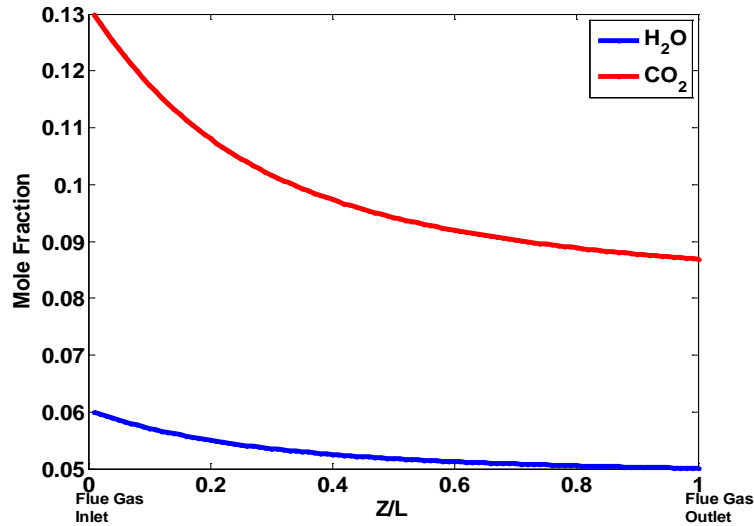


- Gaseous species :  $\text{CO}_2$ ,  $\text{N}_2$ ,  $\text{H}_2\text{O}$
- Solid phase components: bicarbonate, carbamate, and physisorbed water.
- Transient species conservation and energy balance equations for both gas and solid phases in all three regions.

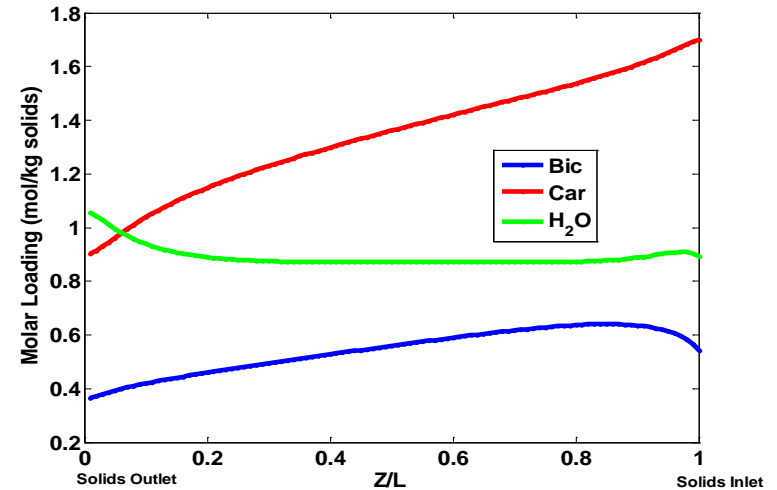
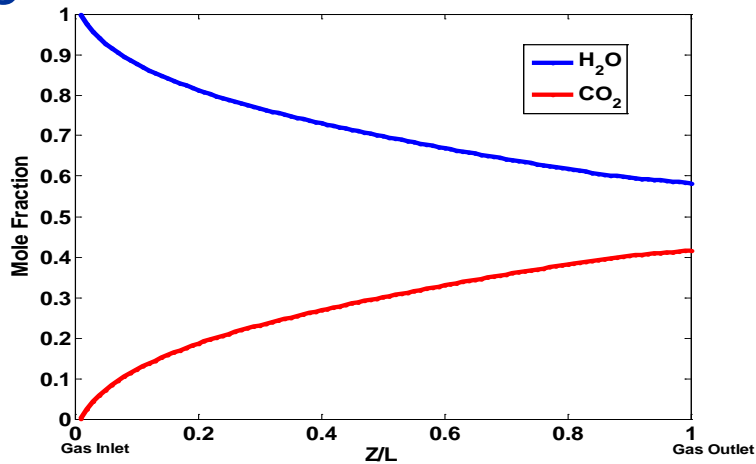
\*Lee, A.; Miller, D. A One-Dimensional (1-D) Three Region Model for a Bubbling Fluidized Bed Adsorber. *Ind. Eng. Chem. Res.* 52, 469-484, 2013

# Bubbling Bed Model : Results

## Adsorber



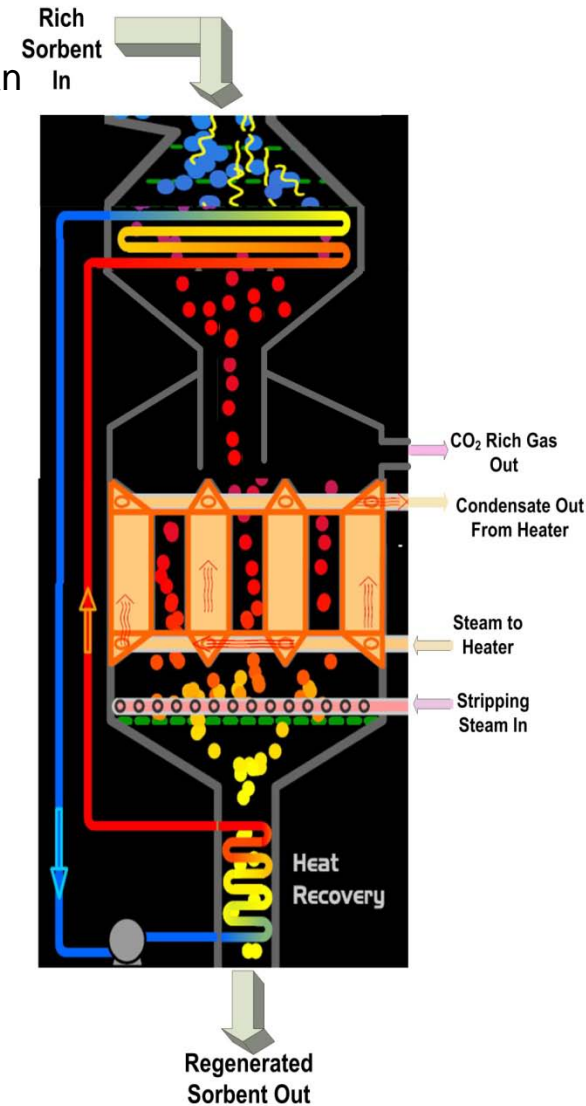
## Regenerator



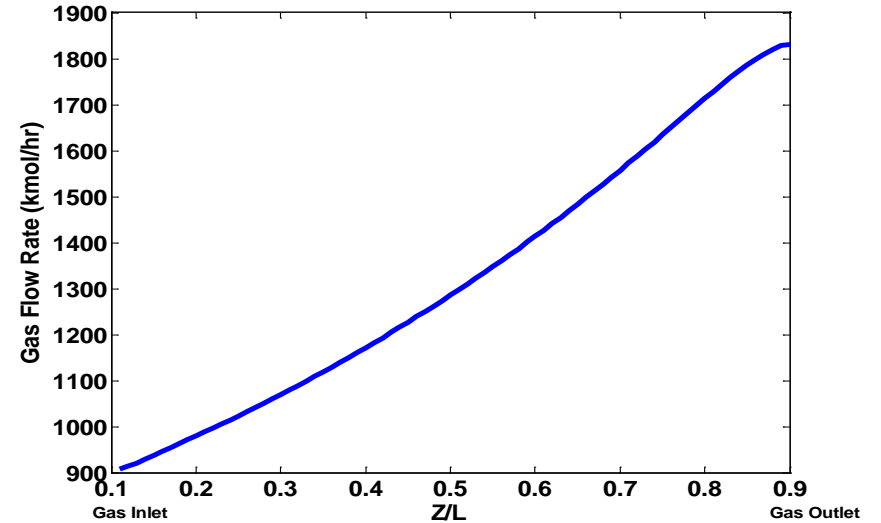
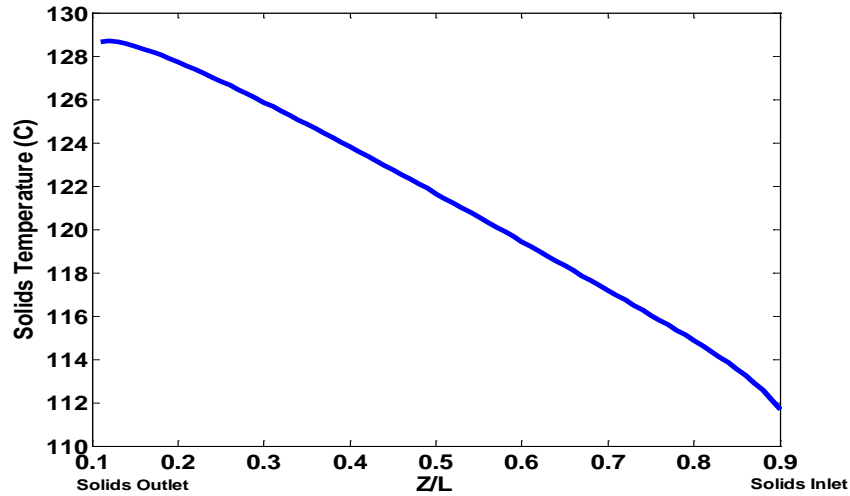
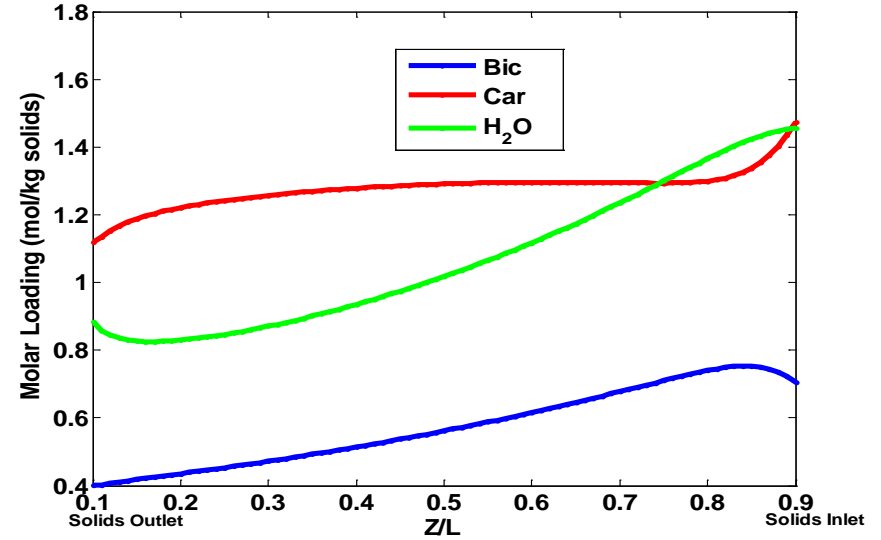
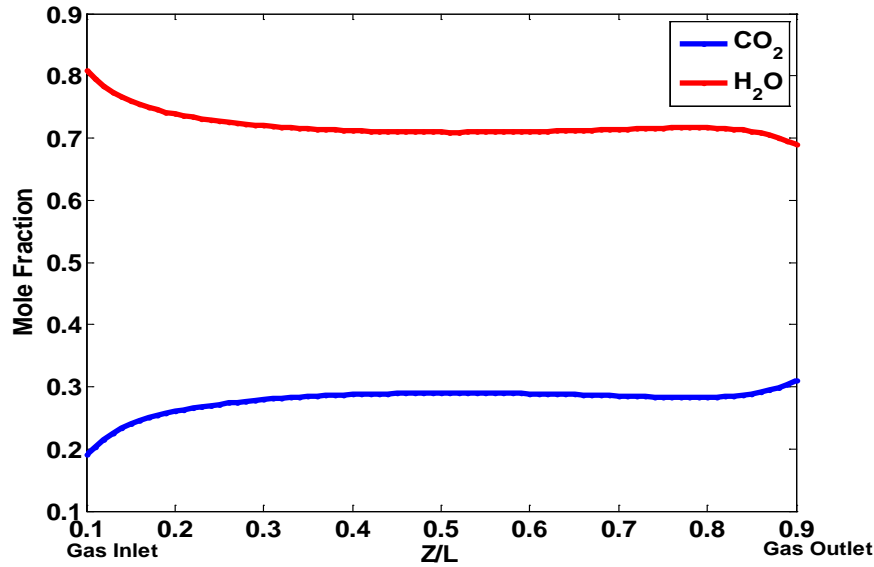


# Development of Moving Bed Model

- A 1-d two-phase model of the moving bed model with embedded heat exchanger mainly for regenerator
- Integrated pre and post-heat exchangers are considered for heat recovery
- Gas and solids flows are modeled by plug flow model with axial dispersion
- For pressure drop calculation, a modified Ergun equation by using the slip velocity between the solids and gas is used instead of the superficial fluid velocity
- Energy balance equations consider heat transfer between solid and gas and tube wall and the mixed phase
- Heat transfer coefficient between the mixed phase and the tube wall is calculated by a modified packet-renewal theory
- Bed hydrodynamics are described by analogy to fixed bed and fluidized bed systems
- Reaction kinetics are similar to the bubbling bed model



# Moving Bed Regenerator: Results



# Solid Sorbent Models: Balance of the Plant

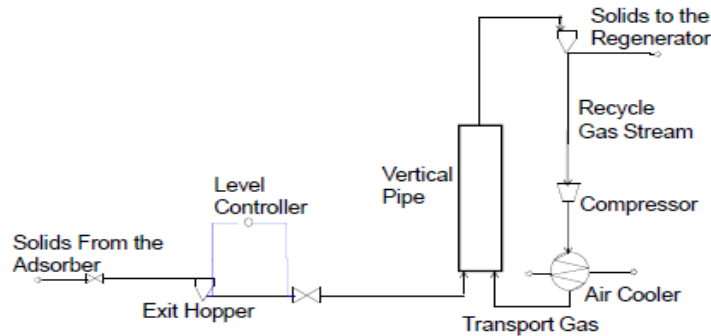
## Heat-Recovery System

- Dynamic model of heat recovery system including pre and post-heat exchangers has been completed

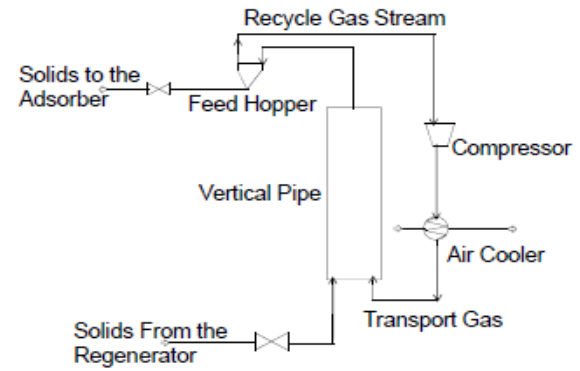
## Solids Transport

- Model of pneumatic transport system has been completed by considering various options for transport gas with the design objective of minimizing auxiliary power consumption

### Adsorber to Regenerator

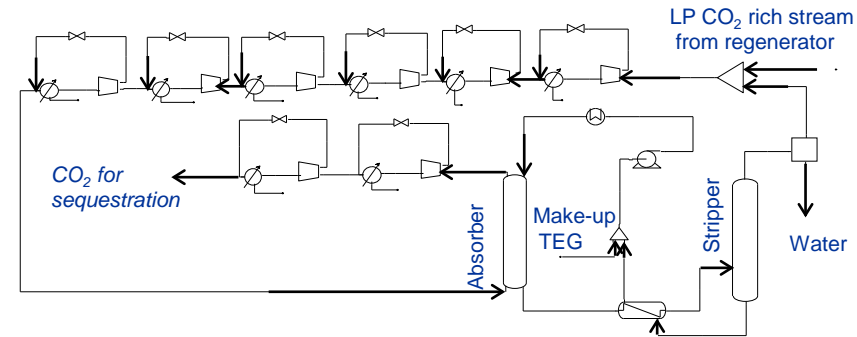


### Regenerator to Adsorber

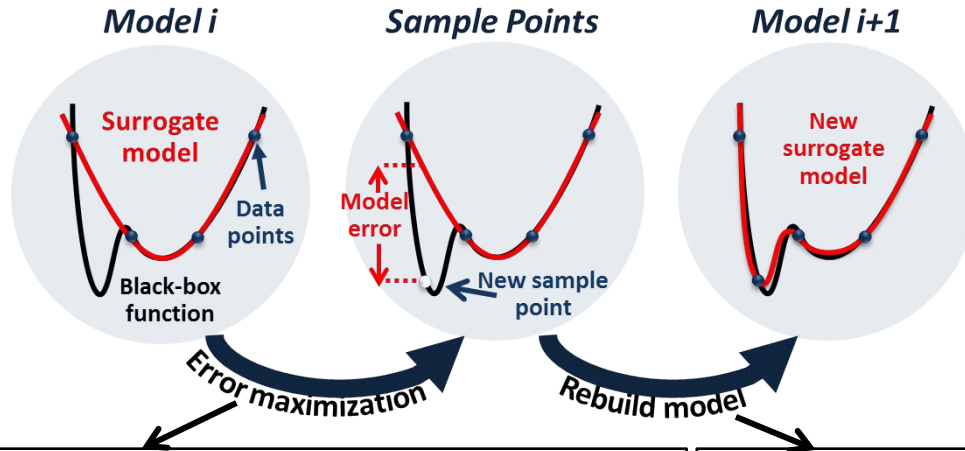


## CO<sub>2</sub> Compression System

- Multi-stage integral gear compressor with inter-stage coolers, recycle valves
- Glycol absorption system modeled for moisture control in the sequestration-ready CO<sub>2</sub>
- Typical performance curves obtained from a commercial vendor



# Automated Learning of Algebraic Models for Optimization



**For building accurate, simple algebraic surrogate models of simulated processes**

$$\max_x \left( \frac{z(x) - \hat{z}(x)}{z(x)} \right)^2$$

Surrogate model  
 Simulation/black-box

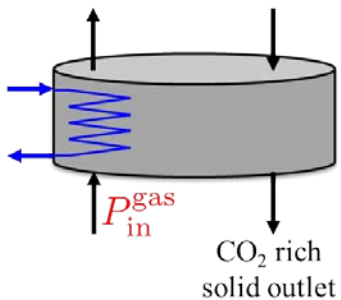
**Step 1: Define a large set of potential basis functions**

$$\hat{z}(x) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1 x_2 + \beta_4 \frac{x_1}{x_2} + \beta_5 \frac{x_2}{x_1} + \beta_6 e^{x_1} + \beta_7 e^{x_2} + \dots$$

**Step 2: Model reduction**

$$\hat{z}(x) = \beta_0 + \beta_2 x_2 + \beta_5 \frac{x_2}{x_1} + \beta_7 e^{x_2}$$

## Example Model: BFB Adsorber Inlet Gas Pressure



- ACM Simulation
- >900 terms possible
- 14 input variables
- 0.13% error

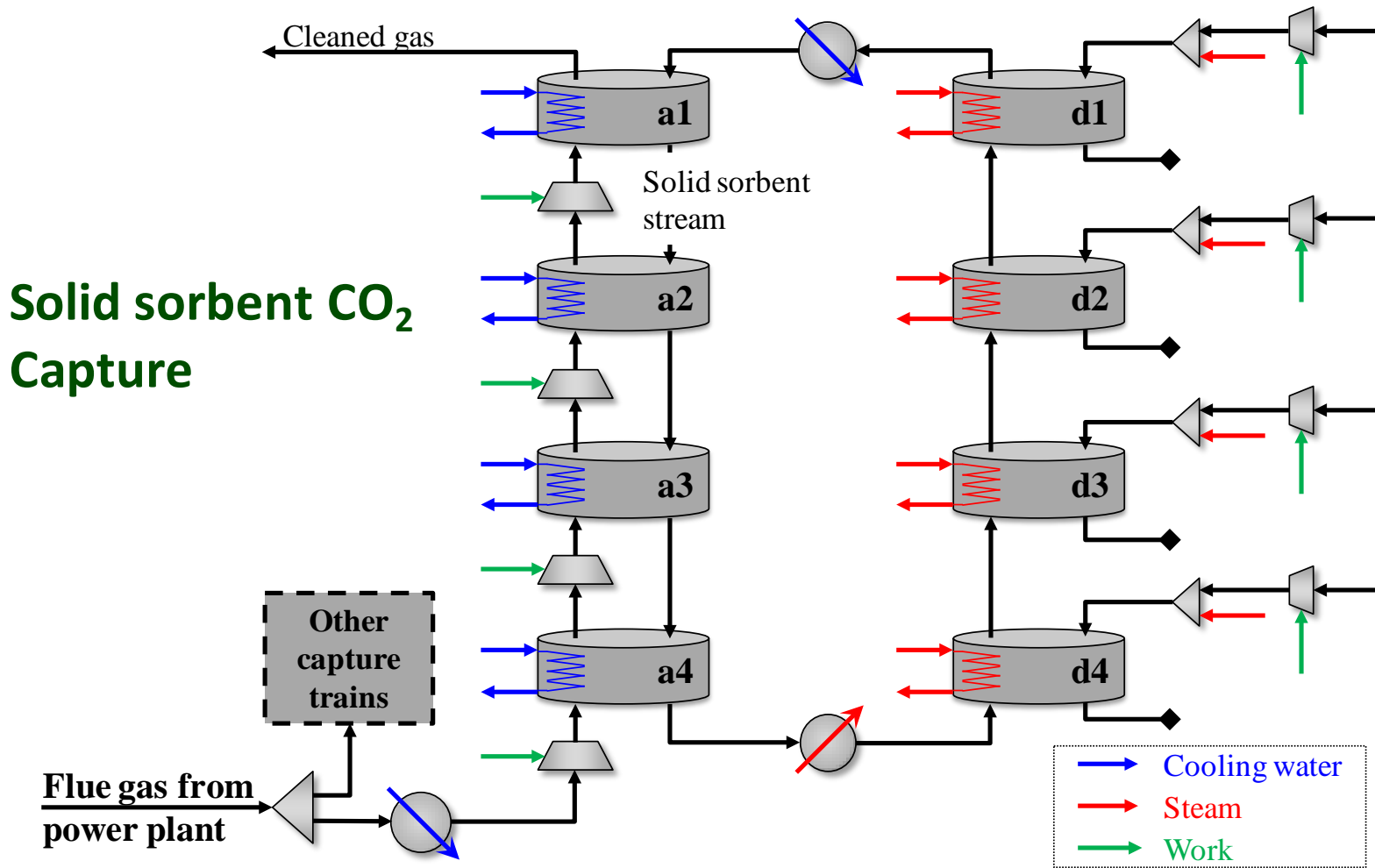
Pressure drop across length of bed

$$\hat{P}_{\text{in}}^{\text{gas}} = P_{\text{out}}^{\text{gas}} + 0.019 L_b + 0.0055 \sqrt{D_T}$$

Proportional to outlet pressure

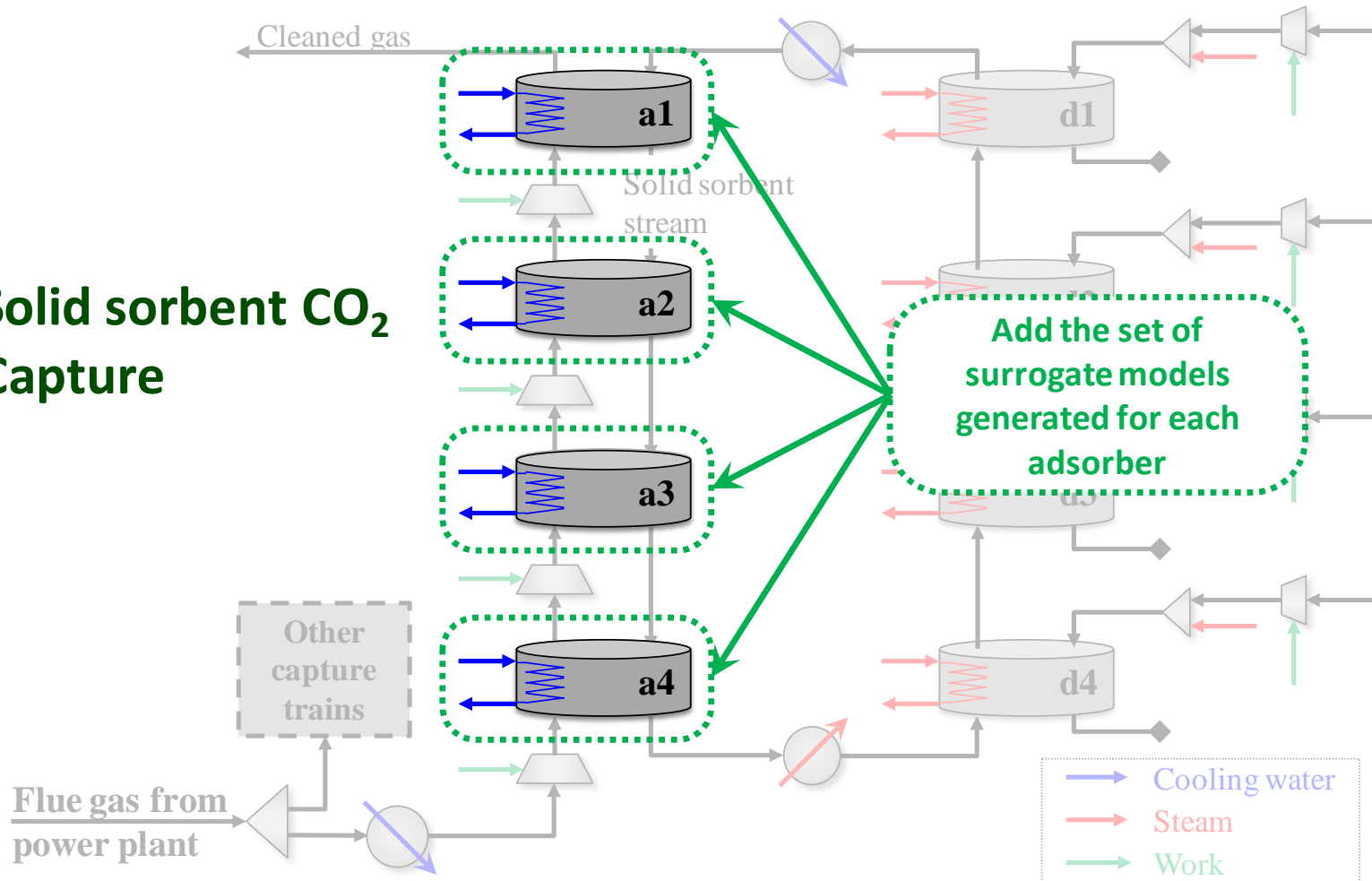
Pressure drop due to bed diameter

# Superstructure Formulation & Optimization

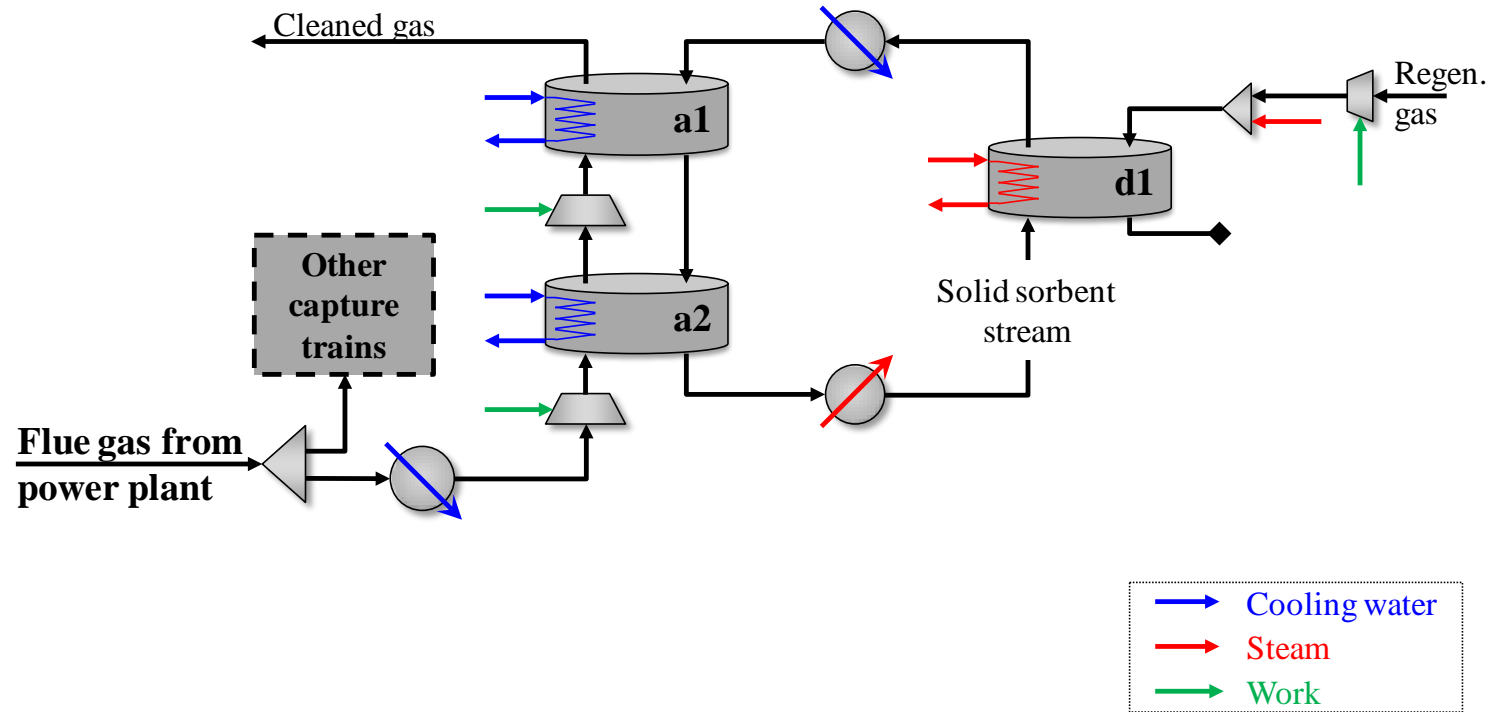


# Insert Algebraic Surrogates into Superstructure

## Solid sorbent CO<sub>2</sub> Capture

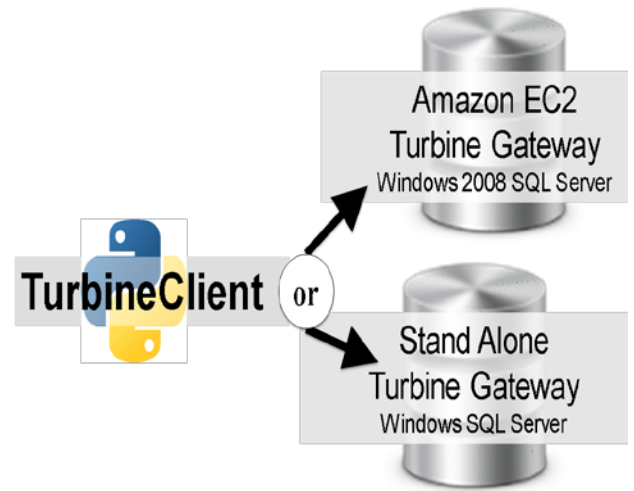
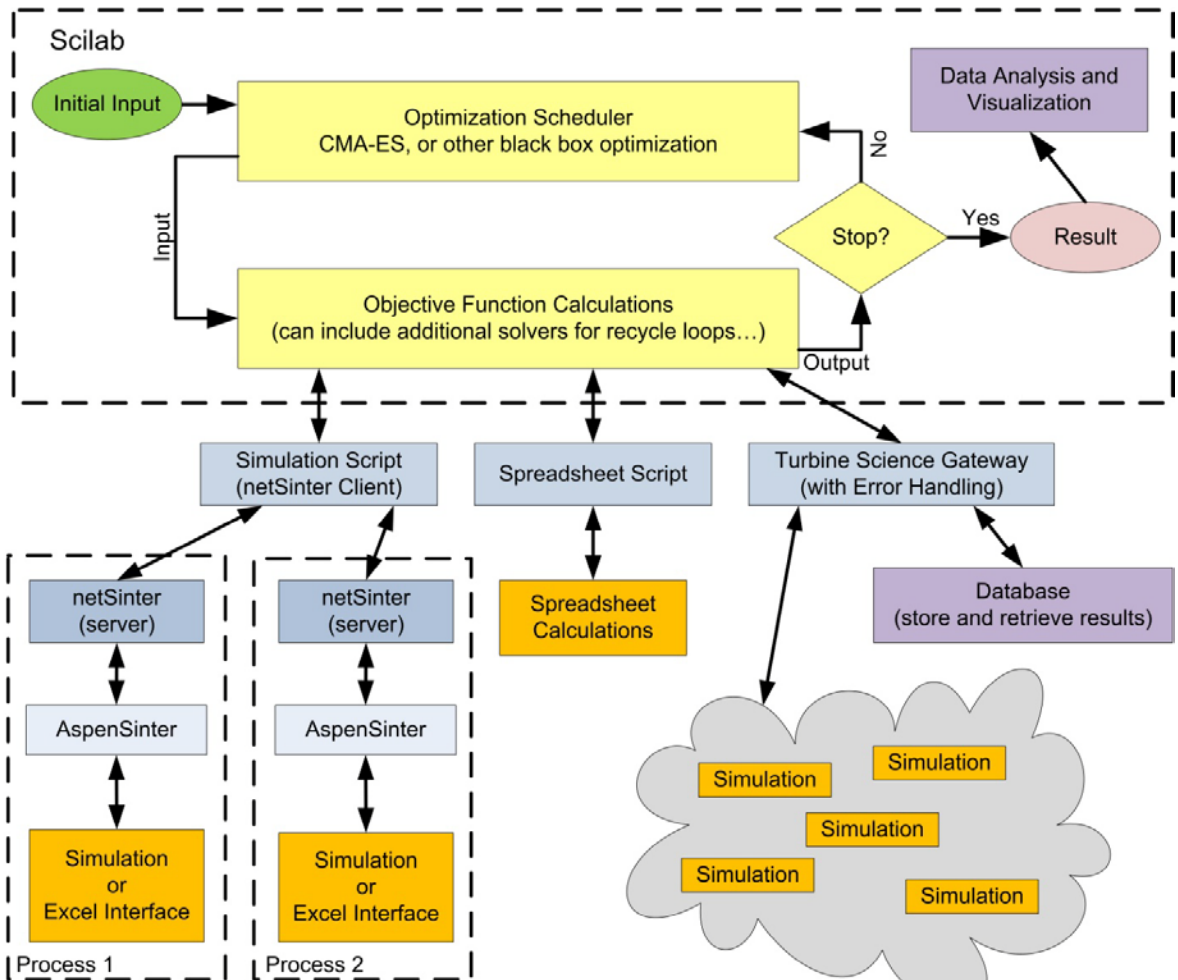


# Initial Superstructure Solution





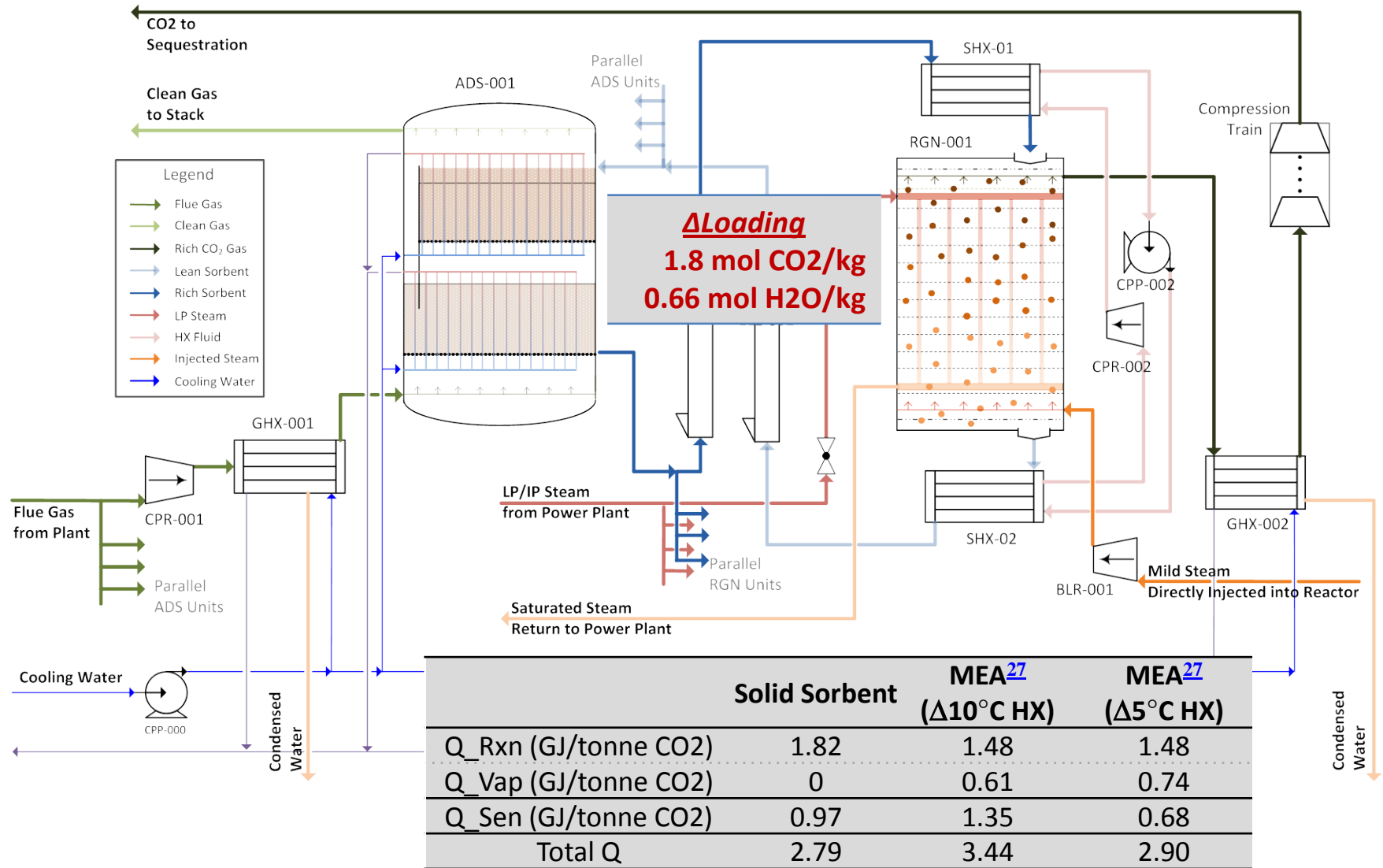
# Simulation-Based Optimization: Verify Solution



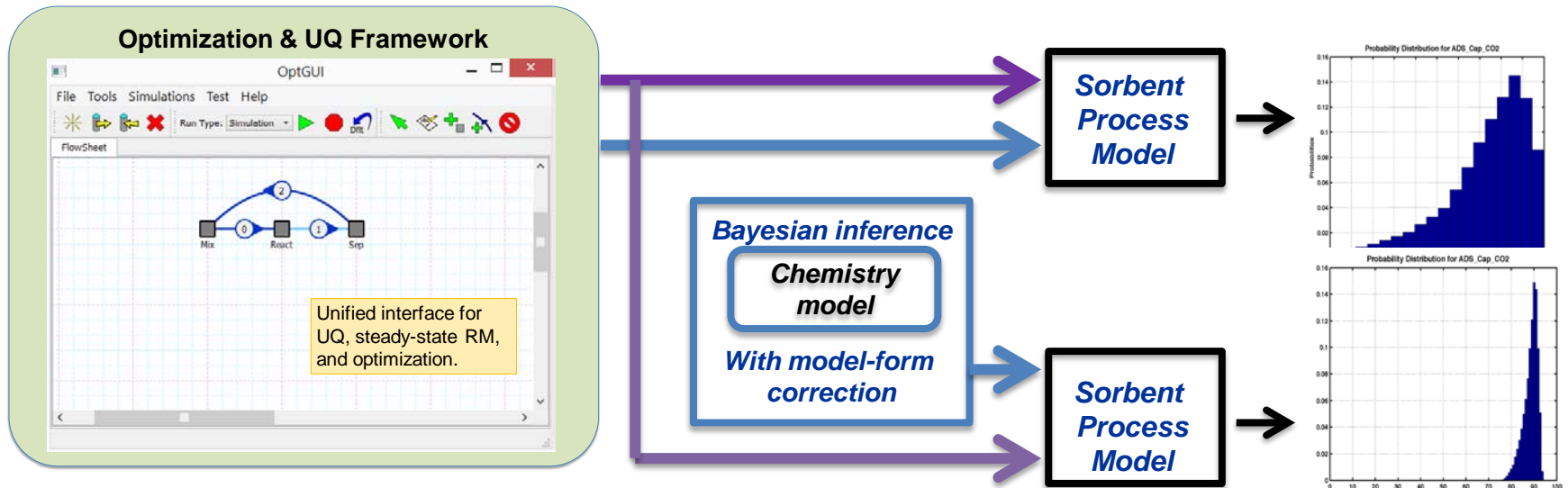
Parallel Simulations (can be run on separate computers)...

Parallel Simulations...

# Optimized Process Developed using CCSI Toolset



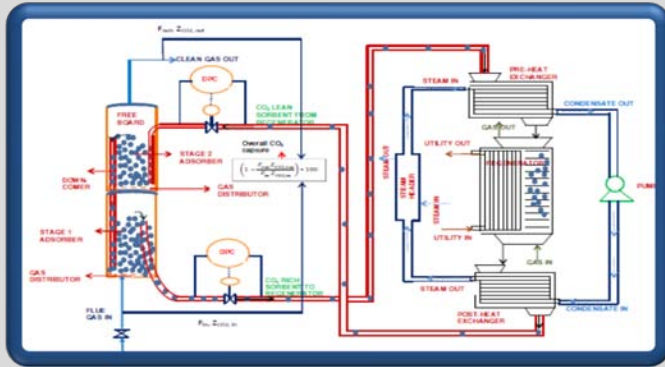
# Multi-Scale Uncertainty Quantification Framework



- **UQ for basic data models**
  - Bayesian UQ methodology
  - Integration of model form discrepancy into process & CFD models
- **UQ for CFD models**
  - Adaptive sampling capability for RM/UQ
  - Bayesian calibration capability
  - UQ of discrepancy between CFD/process models
- **UQ for process models**
  - Integration with optimization platform
  - Optimization under uncertainty

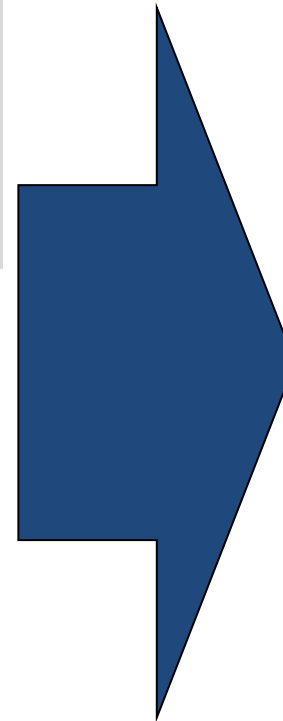
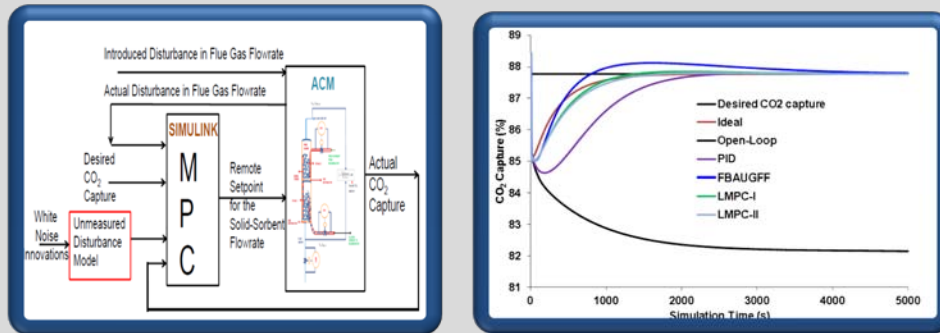
# Dynamic Reduced Models & APC Framework

## 1-D Capture & Compression System Models



## Dynamic Reduced Models

## Advanced Process Control Framework



# Dynamic Reduced Models (D-RMs)

- **Motivation and Approaches**

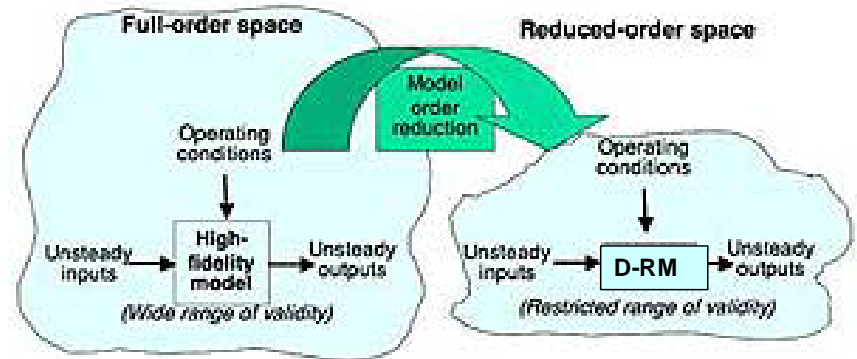
- First-principles dynamic models for CO<sub>2</sub> capture are computationally expensive. D-RMs are very useful for faster computation

- **On-Line Applications:**

- Use in applications such as advanced process control (APC) and real-time optimization (RTO)
- Must be real-time
- Mainly input/output information is important
- *Data-driven* D-RMs based on pre-computed results from repeated simulations of a high-fidelity dynamic model over a range of input/output (I/O) variable values

- **Off-Line Applications:**

- Use as surrogate for process models
- Need not be real-time
- Provides state information
- *Reduced-order* D-RMs based on reduction of state space
  - e.g., Proper Orthogonal Decomposition (POD)





# Dynamic Reduced Models (D-RMs)

## • Tool

### – D-RM Builder for On-Line Applications

- Use high-fidelity ACM/APD models embedded in Simulink to create D-RMs as MATLAB script files (.m files)

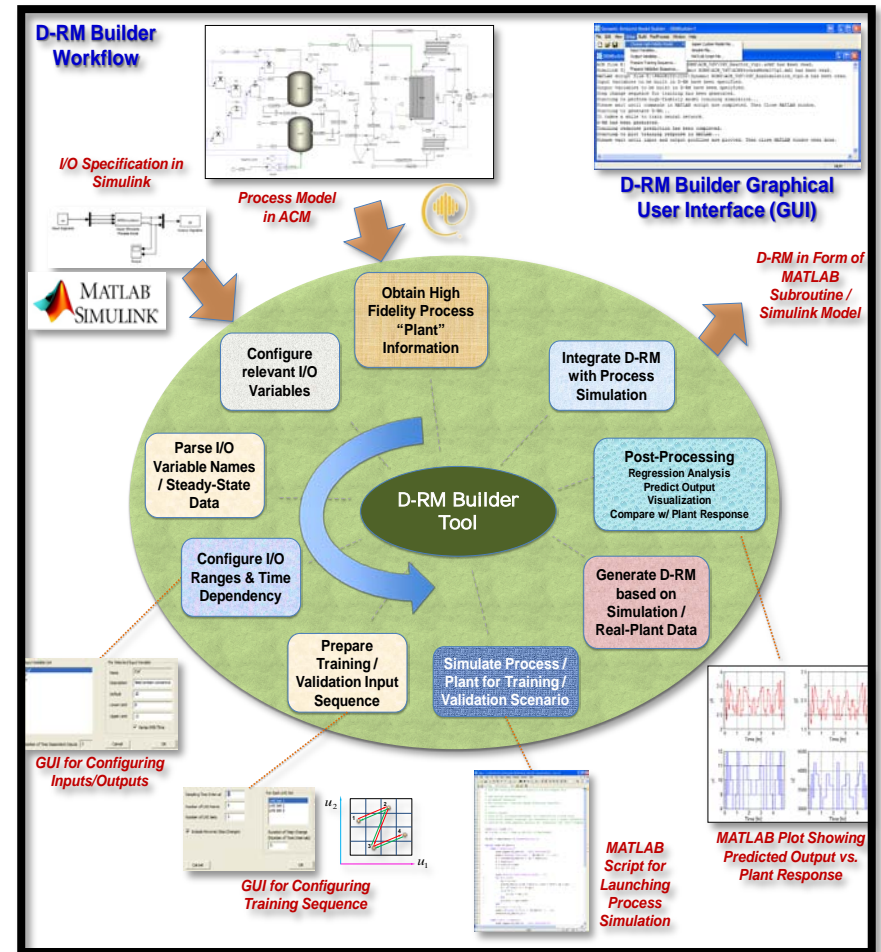
## • Accomplishments

### – Data-driven Black Box

- Implemented Nonlinear Autoregressive Moving Average (NARMA) based on Neural Networks
- Implemented Decoupled A-B Net
  - Linear state-space (Laguerre)
  - Nonlinear mapping from state-space to output using Neural Network

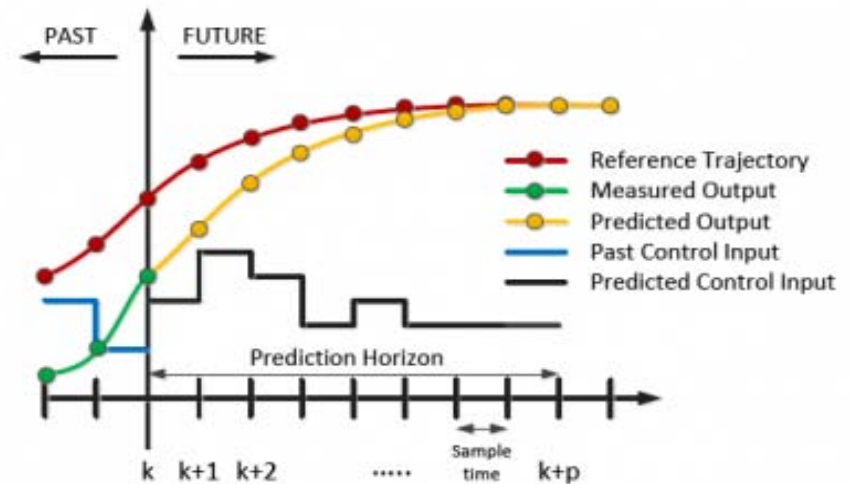
### – D-RM Builder

- Developed preliminary GUI
- Tested on several benchmarks



# Advanced Process Control Framework

- **Goal**
  - Develop estimator-based advanced process control (APC) framework using D-RM models
- **Approaches**
  - Model predictive control (MPC) with input/output constraints
  - Nonlinear state-estimation
    - Recursive: Extended or Unscented Kalman Filter
    - Optimization-based: Moving Horizon Estimation
  - Covariance estimation
    - Autocovariance least-squares (ALS)
- **Tools**
  - APC Framework Tool
    - Use data-driven D-RMs as prediction models embedded in Simulink for real-time APC
    - Option of compiled MATLAB files for high execution speed



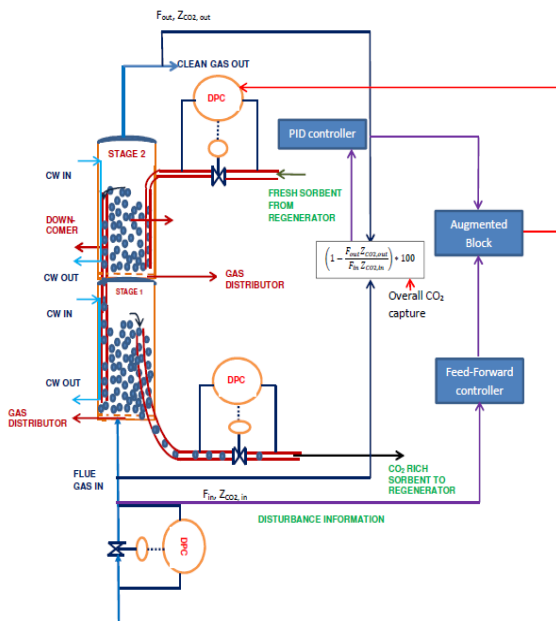
**Model Predictive Control**



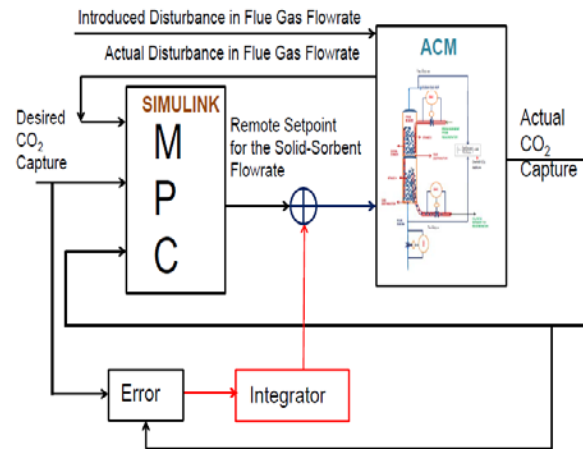
# Controller Design for Maintaining CO<sub>2</sub> Capture

## 1. Traditional PID Control

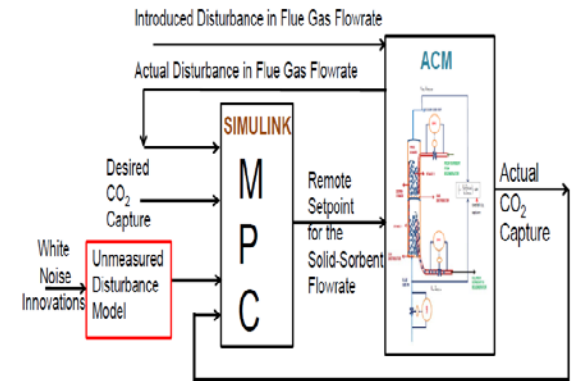
## 2. FEEDBACK-AUGMENTED FEEDFORWARD CONTROLLER



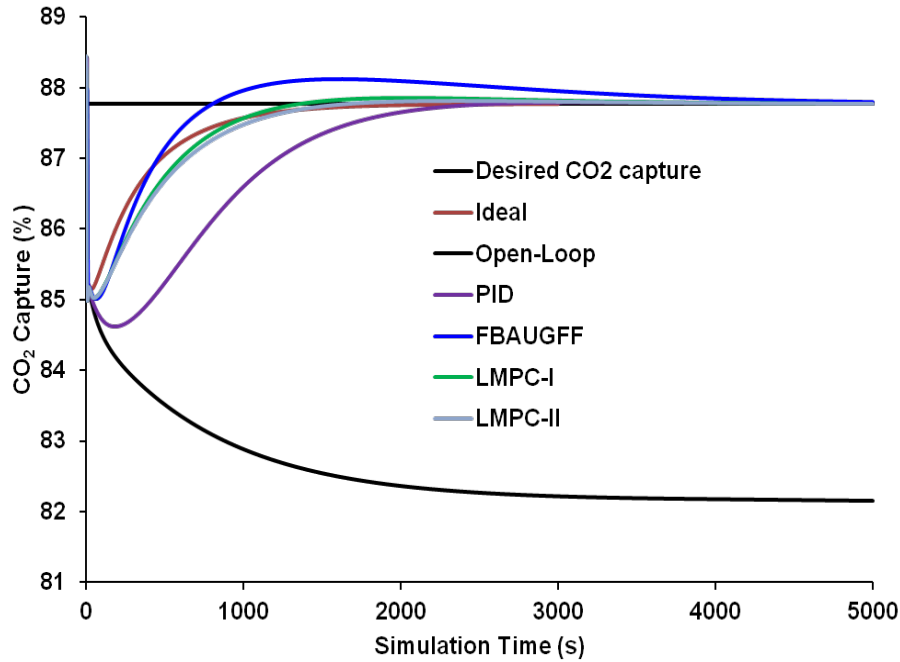
## 3. Offset-free LMPC Using an Integrator



## 4. Offset-free LMPC Using Unmeasured Disturbance



# CONTROLLER PERFORMANCE COMPARISON



Control performances of LMPC-I and LMPC-II are superior to others

Control Performance Table

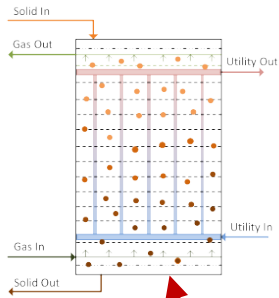
CONTROLLER	IAE	ISE	ITAE
	(hr)	(hr)	(hr <sup>2</sup> )
(1) PID	0.8111	1.7551	1.12E-04
(2) FBAUGFF	0.4751	<b>0.5502</b>	6.60E-05
(3) LMPC-I	<b>0.3913</b>	0.6138	<b>5.57E-05</b>
(4) LMPC-II	0.4007	0.6386	6.30E-05

# CFD models to reduce time for design/troubleshooting

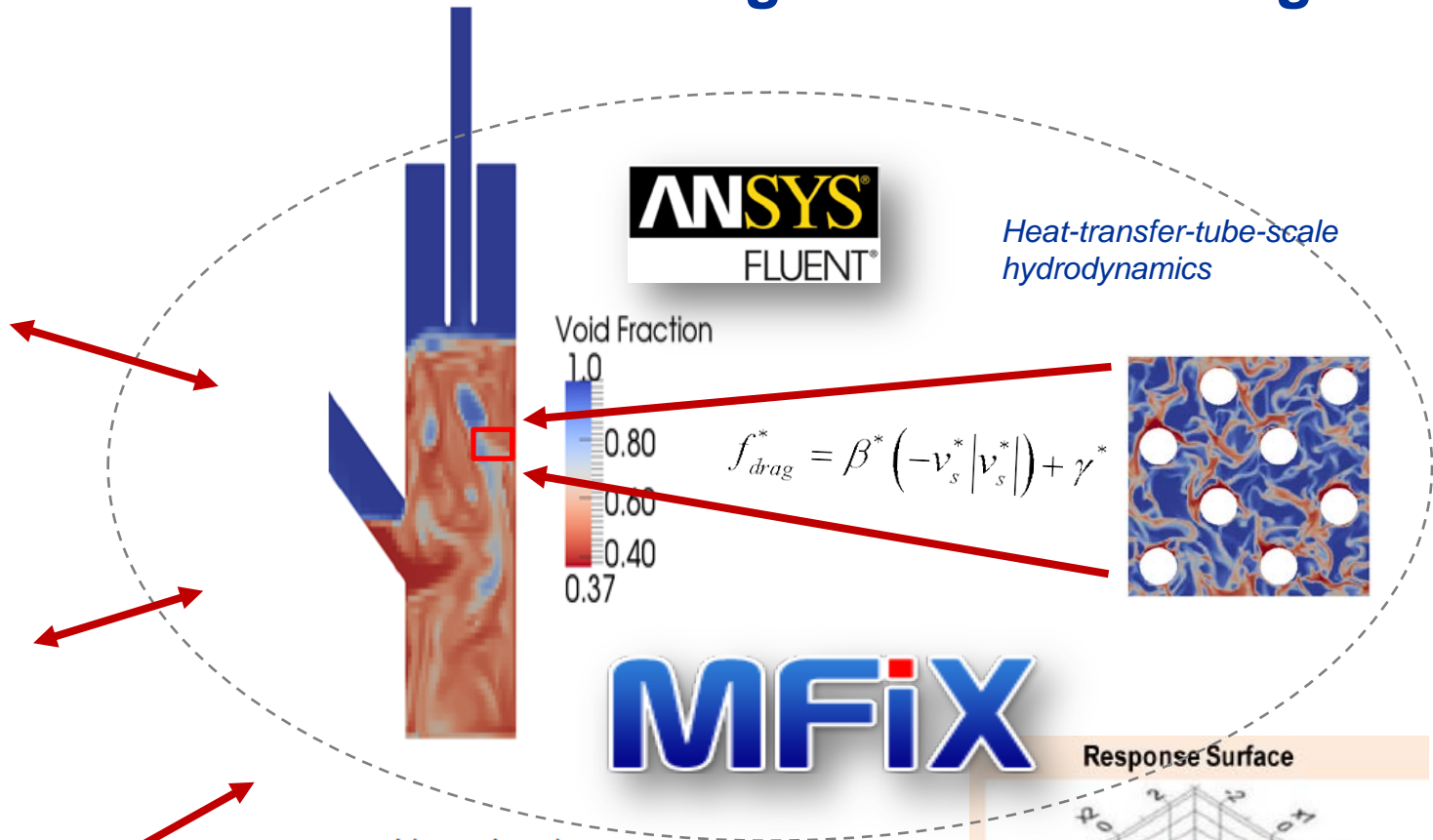
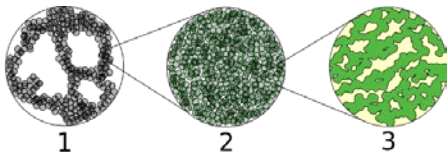
Experimental Validation



Process Model



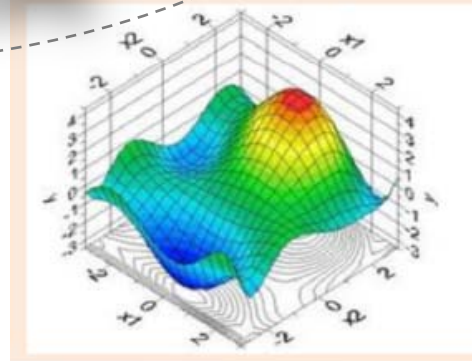
**SORBENTFIT**

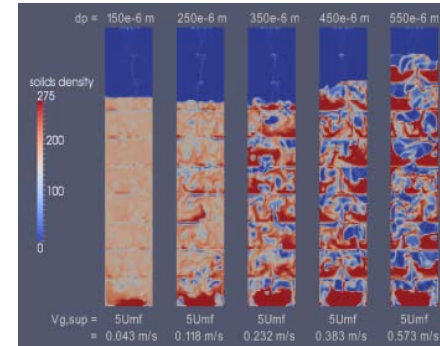
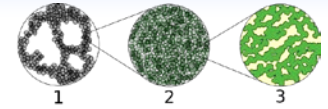
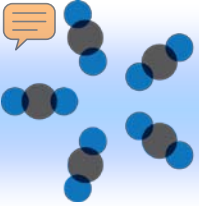


**MFiX**

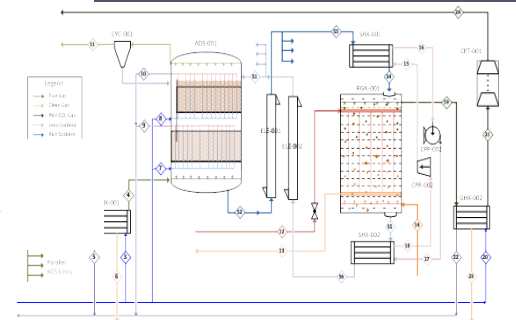
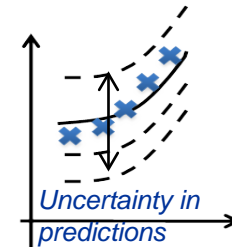
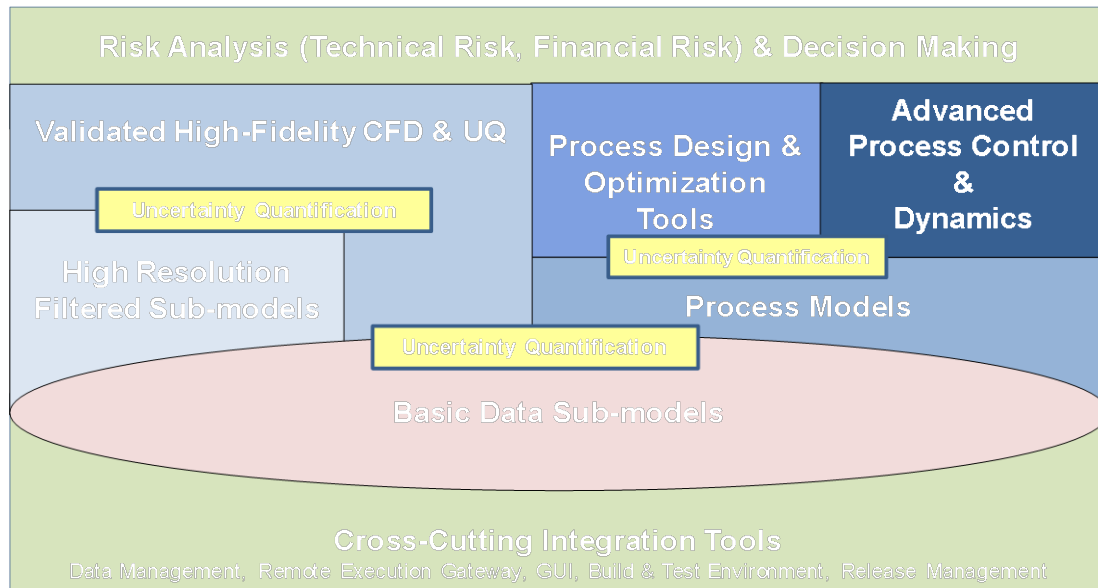
Void Fraction along vertical center plane

Response Surface

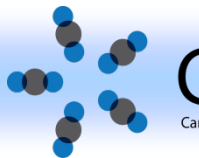
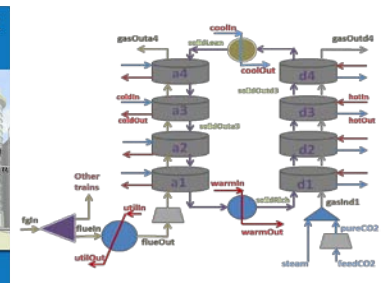




- Initial toolset released Oct. 2012, 1 year ahead of schedule due to industry request for early access
  - 3 companies already have already licensed
  - Other companies pursuing license
- Additional releases planned for Fall 2013, 2014, 2015.
- Final release planned for Jan. 2016



### Automated Learning of Algebraic Models for Optimization





# ... and the people who made that happen!



# Thank you!

## Disclaimer

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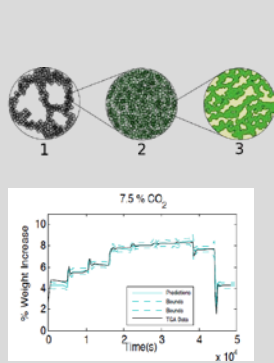
# Backup slides



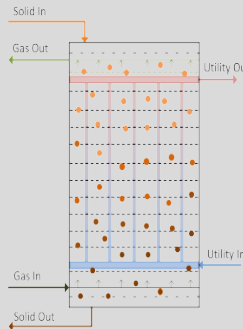


# Advanced Process Systems Engineering Approaches

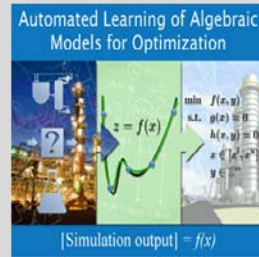
## Basic Data Models



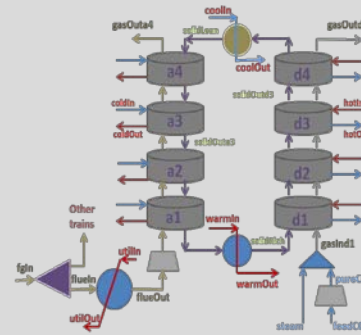
## Process Models



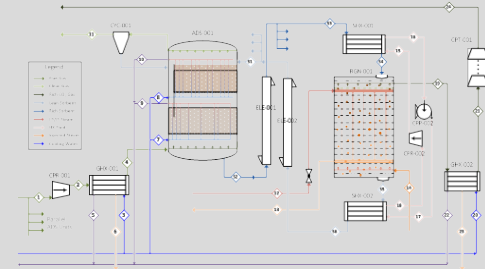
## Algebraic Surrogate Models



## Superstructure Optimization



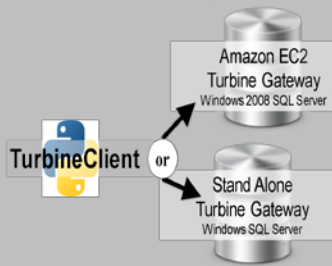
## Optimal Process



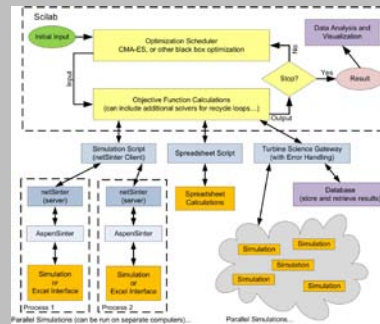
SORBENTFIT



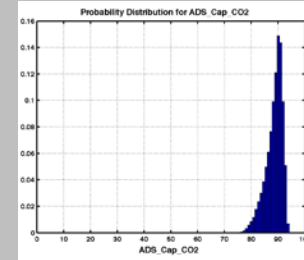
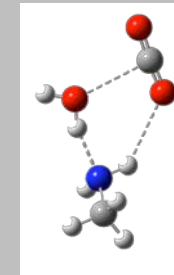
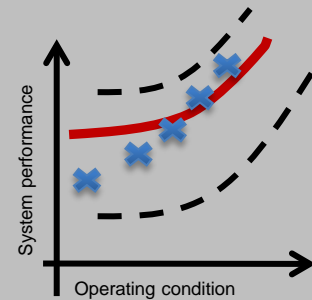
## Simulation Gateway



## Simulation-Based DFO Framework



## Uncertainty Quantification with Bayesian Calibration



# CONSERVATION EQUATIONS

## Bubble Region :

### Gaseous Components

$$\frac{\partial(\delta V C_{b,i})}{\partial t} + \frac{V}{A} \frac{\partial(y_{b,i} G_{b,i})}{\partial x} + \delta V K_{bc,i} (C_{b,i} - C_{c,i}) + K_{g,bulk} = 0$$

$$\frac{\partial(C_{P,g} C_{bt} \delta V (T_{g,b} - T_{ref}))}{\partial t} + \frac{\partial(C_{P,g} G_b (T_{g,b} - T_{ref}))}{\partial x} + \delta A H_{bc} (T_{g,b} - T_{g,c}) - H_{g,bulk} = 0$$

## Cloud-wake Region :

### Gaseous Components

$$\frac{\partial(f_{cw} \delta \varepsilon_d V C_{c,i})}{\partial t} - V \delta K_{bc,i} (C_{b,i} - C_{c,i}) + V \delta K_{ce,i} (C_{c,i} - C_{e,i}) + V \delta (1 - \varepsilon_d) f_{cw} r_{g,c} = 0$$

$$\begin{aligned} & \frac{\partial(C_{P,g} C_{ct} V \delta f_{cw} e_d (T_{g,c} - T_{ref}))}{\partial t} - A \delta H_{bc} (T_{g,b} - T_{g,c}) + A \delta H_{ce} (T_{g,c} - T_{g,e}) + A f_{cw} \delta (1 - \varepsilon_d) \rho_s a_p h_p (T_{g,c} - T_{s,c}) \\ & - f_{cw} \delta (1 - \varepsilon_d) A \sum_j r_{g,c,i} C_{p,g,c,i} (T_{g,c} - T_{ref}) = 0 \end{aligned}$$

### Adsorbed Species

$$\frac{\partial(V f_{cw} \delta (1 - \varepsilon_d) n_{c,j})}{\partial t} - \frac{V}{\rho_s} \frac{\partial(n_{c,j})_c}{\partial x} + K_{s,bulk,j} + V \delta K_{cebs} (n_{c,j} - n_{e,j}) - V f_{cw} \delta (1 - \varepsilon_d) r_{s,c} = 0$$

$$\begin{aligned} & \frac{\partial(A \Delta x f_{cw} \delta \rho_s C_{P,s} (1 - \varepsilon_d) (T_{s,c} - T_{ref}))}{\partial t} + A \frac{\partial(J_c C_{P,s} (T_{s,c} - T_{ref}) + h_{ads,c})}{\partial x} + H_{s,bulk} \\ & + A \delta \rho_s K_{cebs} (C_{P,s} (T_{s,c} - T_{ref}) + h_{ads,c} - C_{P,s} (T_{s,e} - T_{ref}) + h_{ads,e}) \\ & + f_{cw} \delta (1 - \varepsilon_d) A \sum_j r_{g,c,i} C_{p,g,c,i} (T_{g,c} - T_{ref}) - A f_{cw} \delta (1 - \varepsilon_d) \rho_s a_p h_p (T_{g,c} - T_{s,c}) = 0 \end{aligned}$$

# CONSERVATION EQUATIONS CONTD.

## Emulsion Region :

### Gaseous Components

$$\frac{\partial(V(1 - f_{cw}\delta - \delta)\varepsilon_d C_{e,i})}{\partial t} - \delta AK_{ce,i}(C_{c,i} - C_{e,i}) - K_{g,bulk} + (1 - f_{cw}\delta - \delta)A(1 - \varepsilon_d)r_{g,e} = 0$$

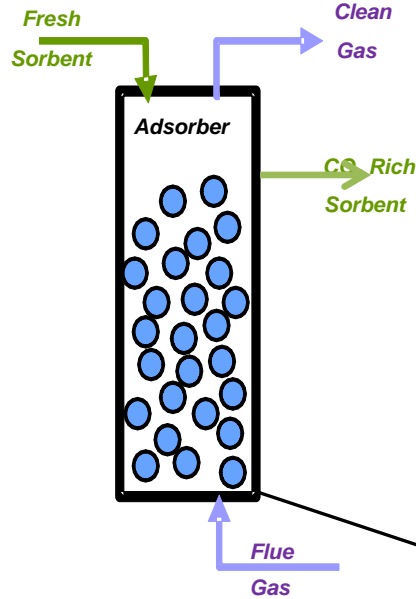
$$\frac{\partial(C_{p,g}C_{et}V(1 - f_{cw}\delta - \delta)\varepsilon_d(T_{g,e} - T_{ref}))}{\partial t} - A\delta H_{ce}(T_{g,c} - T_{g,e}) + H_{g,bulk} + (1 - f_{cw}\delta - \delta)(1 - \varepsilon_d)A\rho_s a_p h_p(T_{g,e} - T_{s,e}) - (1 - f_{cw}\delta - \delta)(1 - \varepsilon_d)A \sum_j r_{g,e,i} C_{p,g,e,i}(T_{g,e} - T_{ref}) = 0$$

### Adsorbed Species

$$\frac{\partial(V(1 - f_{cw}\delta - \delta)(1 - \varepsilon_d)n_{e,j})}{\partial t} + \frac{V}{\rho_s} \frac{\partial(n_{e,j}J_e)}{\partial x} - K_{s,bulk,j} - V\delta K_{cebs}(n_{c,j} - n_{e,j}) - V(1 - f_{cw}\delta - \delta)(1 - \varepsilon_d)r_{s,e} = 0$$

$$\frac{\partial(C_{p,s}\rho_s A(1 - f_{cw}\delta - \delta)(1 - \varepsilon_d)(T_{s,e} - T_{ref}))}{\partial t} + A \frac{\partial(J_e C_{p,s}(T_{s,e} - T_{ref}) + h_{ads,e})}{\partial x} - H_{s,bulk} - A\delta\rho_s K_{cebs}(C_{p,s}(T_{s,c} - T_{ref}) + h_{ads,c} - C_{p,s}(T_{s,e} - T_{ref}) + h_{ads,e}) + (1 - f_{cw}\delta - \delta)(1 - \varepsilon_d)A \sum_j r_{g,e,i} C_{p,g,e,i}(T_{g,e} - T_{ref}) - (1 - f_{cw}\delta - \delta)(1 - \varepsilon_d)A\rho_s a_p h_p(T_{g,e} - T_{s,e}) - \pi d_{HX} h_{t,x} \Delta T_{hx} N_{HX} C_r = 0$$

# HYDRODYNAMIC MODEL



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

where  $\gamma_1 = \frac{2.56 \times 10^{-2}}{v_{mf}} \sqrt{\frac{D_t}{g}}$  and  $\gamma_{3,x} = \sqrt{\gamma_1^2 + 4 \frac{d_{b,m,x}}{D_t}}$

$$d_{b,e,x} = \frac{D_t}{4} (-\gamma_1 + \gamma_{3,x})^2$$

$$d_{b,m,x} = 2.59 g^{-0.2} (A_x [v_{g,x} - v_{e,x}])^{0.4}$$

$$d_{b,0} = 1.38 g^{-0.2} (a_o [v_{g,0} - v_{e,0}])^{0.4}$$

Mori and Wen (1975)

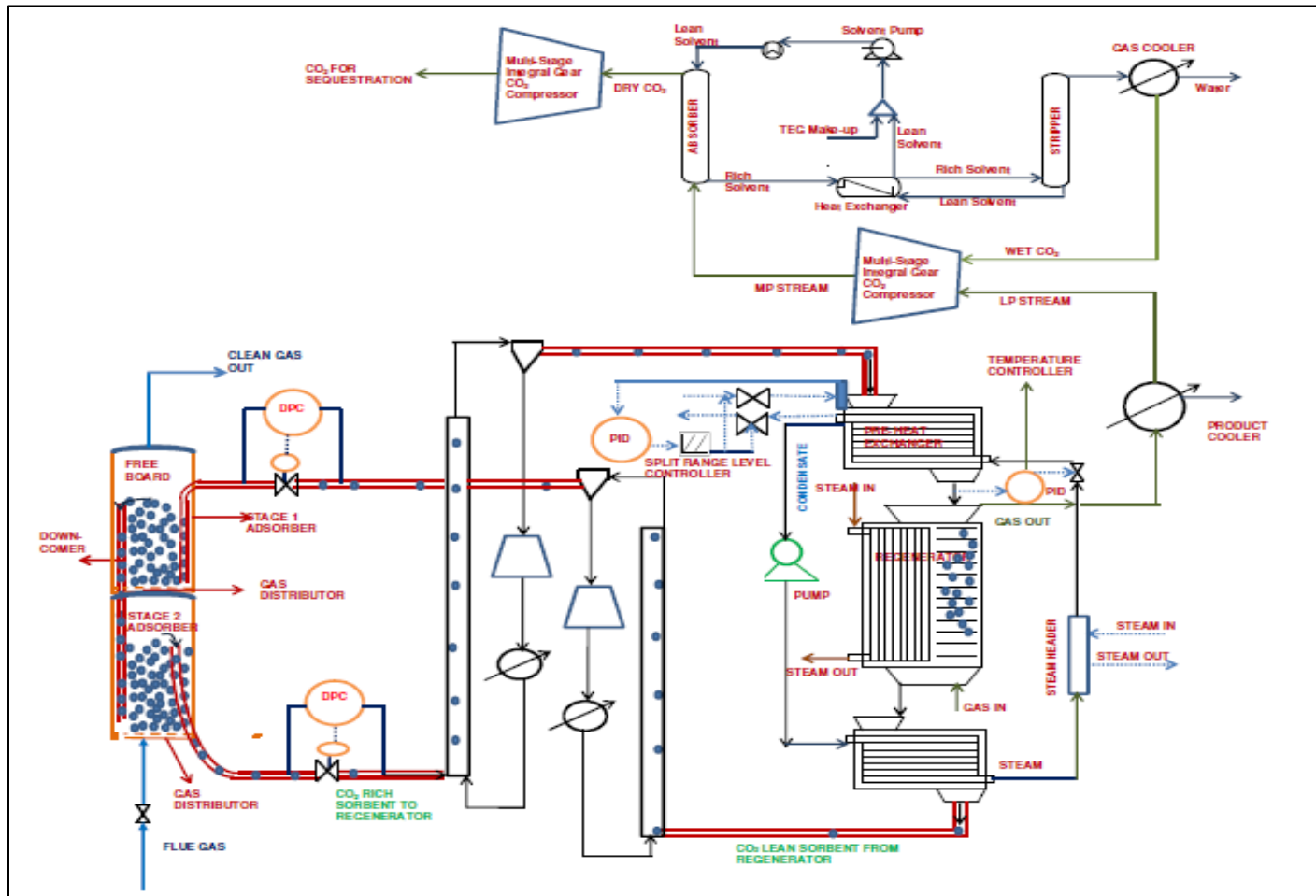
$$v_{b,x} = v_{g,x} - v_{mf} + 0.35 \sqrt{g D_{t,h}}$$

$$K_{bc,j,x} = 1.32 \times 4.5 \frac{v_{mf}}{d_{b,x}} + 5.85 \frac{D_{j,x}^{0.5} g^{0.25}}{d_{b,x}^{5/4}}$$

$$K_{ce,j,x} = 6.78 \sqrt{\frac{\epsilon_{d,x}^2 D_{j,x} v_{b,x}}{d_{b,x}^3}}$$

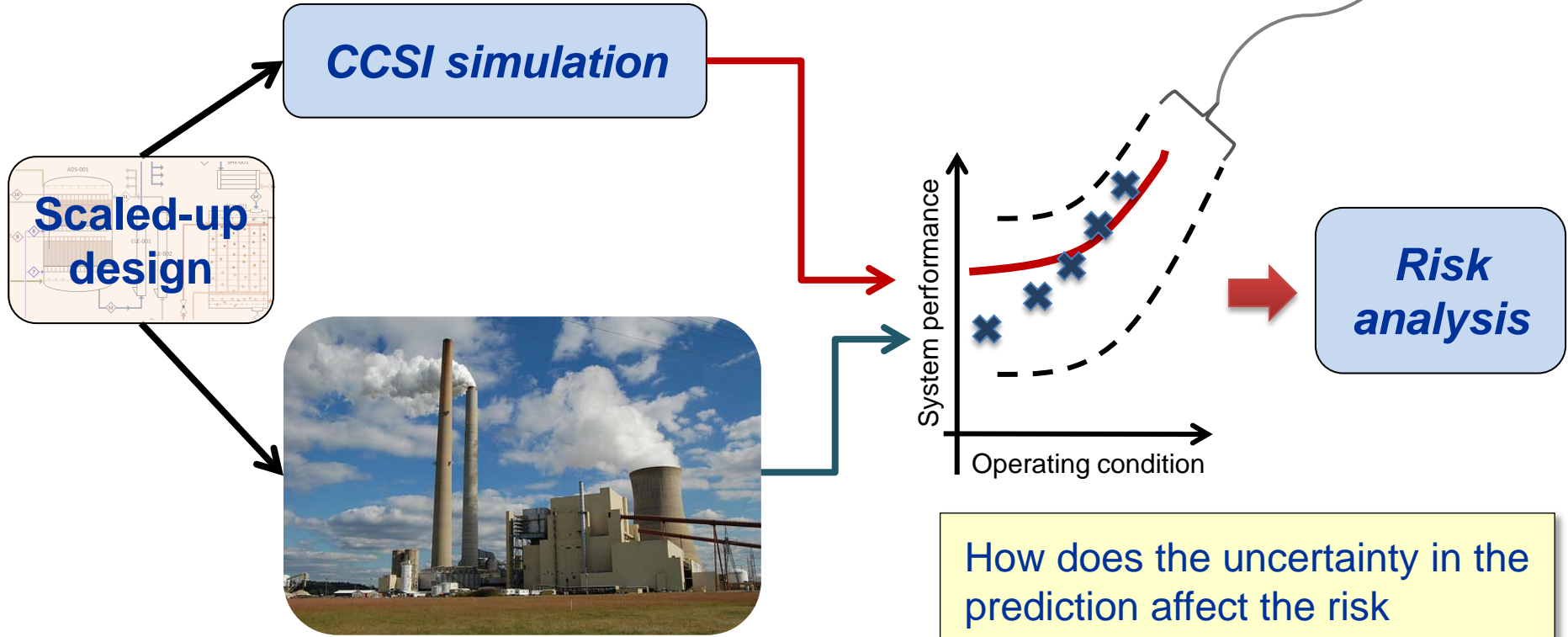
Sit and Grace (1981)

# Process Model of the Integrated System



# Uncertainty Quantification: How certain are we that our model can predict the system performance accurately?

- How to quantify these error bounds *a priori*?
- How to reduce these bounds?



How does the uncertainty in the prediction affect the risk assessment outcome?