

### Validation and Uncertainty Quantification of a High-Fidelity Model of a MEA-Based CO<sub>2</sub> Capture System

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**U.S. DEPARTMENT OF** 

**AICHE Annual Meeting 2014** Atlanta, GA

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# Outline

- Motivation
- Approach
  - Deterministic model
  - Uncertainty Quantification
- Results
  - Holdup
  - Pressure Drop
  - Interfacial Area
  - Mass Transfer Coefficients
  - Uncertainty Propagation
- Conclusion





### **Process Model**

- Hydraulic Model
  - Holdup
  - Pressure Drop

#### • Mass Transfer Model

- Interfacial Area
- Mass Transfer Coefficients
- Heat Transfer Model
  - Heat Transfer Coefficients











## A Close Look on Uncertainty in Modeling: Pressure Drop Model



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### Parametric Uncertainty Propagation



## Overall Approach to UQ

- Deterministic Model Identification
  - Identification of Model and Data
  - Parameter Calibration (with model form correction)
  - Implementation in Aspen Plus<sup>®</sup> (Fortran User Models)
- Parametric Uncertainty Quantification
- Uncertainty Propagation Through Process Model



#### Physical Properties, Hydraulic, and Mass Transfer Models



### Stochastic Modelling Approach



# Holdup Sub-model Uncertainty Quantification













### Step 1 – Model Parameter Calibration: Holdup

2 Parameters Calibrated



## Step 2 - Response Surface Model:Holdup

- 69 Sets of Process Variables
- Uniform Prior Distribution (Monte Carlo Simulation)
  - Sample size = 100
  - ± 20% range assumption from calibrated values
- Results obtained from the deterministic model (6900 points)
- Multivariate Adaptive Regression Splines (MARS) method to fit a response surface



### Step 2 - Response Surface Model: Holdup



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### Step 3 – Bayesian Inference

- Posterior distribution of the parameters are generated by maximizing expectation of finding the experimental data given the uncertainty in observation and initial guess of parametric uncertainty
- Method: Markov Chain Monte Carlo
- Software: PSUADE









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### Pressure Drop

- Billet and Schultes' correlation was evaluated
- Calibration of 1 Parameter
- For holdup, modified Tsai (2010) model was considered



### Interfacial Area

- Tsai (2010) correlation was selected
- No calibration was performed
- Uncertainty considered in 2 Parameters



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## Liquid Side Mass Transfer Coefficient

- None of the existing correlations that were evaluated gave satisfactory result in comparison to the experimental data
- Wang (2013)<sup>3</sup> was selected for being a complementary study to Tsai (2010)
- Calibration of 2 Parameters
- Uncertainty considered in 2 Parameters



### Parametric Uncertainty Propagation

- Posterior distributions from Bayesian Inference are considered
- User models developed in FORTRAN, compiled and used in Aspen Plus environment
- For each set of parameters and process variables, Aspen Workbook was used to run the Aspen simulations











### Initial vs Final Results

(Hold up, interfacial area, and liquid-side mass transfer coefficient only)



### Conclusion

- A methodology for quantification of parametric uncertainty of process models is developed.
- Starting from an initial guess, the methodology generates a more precise estimate of parametric uncertainty if the observation data and their uncertainty are known
- The methodology improves the overall estimate, both deterministic and stochastic, of the key variables.



### Acknowledgment

As part of the National Energy Technology Laboratory's Regional University Alliance (NETLRUA), a collaborative initiative of the NETL, this technical effort was performed under the RES contract DE-FE0004000.

The authors would like to thank Prof. Gary T. Rochelle from The University of Texas at Austin for sharing the Phoenix model. The authors sincerely acknowledge valuable discussions with Prof. Rochelle and Brent Sherman from The University of Texas at Astin.









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# Thank you!

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