

# CCSI

Carbon Capture Simulation Initiative

## Uncertainty Quantification of VLE Models for an MEA System

Josh Morgan<sup>a</sup>, Benjamin Omell<sup>a</sup>, Debangsu Bhattacharyya<sup>a</sup>, Charles Tong<sup>b</sup>, David C. Miller<sup>c</sup>

<sup>a</sup> *Department of Chemical Engineering, West Virginia University, Morgantown, WV 26506, USA*

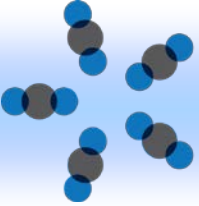
<sup>b</sup> *Lawrence Livermore National Laboratory, Livermore, CA 94550, USA*

<sup>c</sup> *National Energy Technology Laboratory, 626 Cochrans Mill Rd, Pittsburgh, PA 15236, USA*

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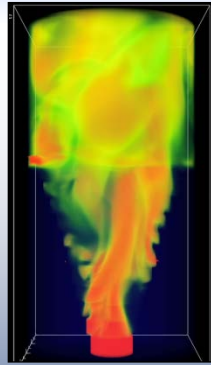
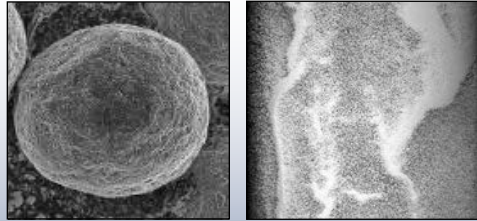


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# CCSI For Accelerating Technology Development

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

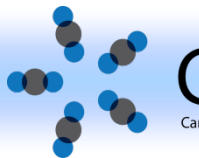
## National Labs



## Academia



## Industry



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# Outline

- Research Objectives and Motivation
- Overall Methodology
- Phoenix Model and e-NRTL Background
- Preliminary Results
  - VLE
  - Heat capacity
  - Heat of absorption
- Future Work

# Research Motivation

- Develop robust algorithm for uncertainty quantification of CO<sub>2</sub> based carbon capture system
- Starting point: “Gold Standard” MEA model
  - 30% aqueous MEA solution is industry standard
- Deterministic models of system have been considered
  - “Phoenix Model” (Rochelle Group at UT-Austin) used as baseline in this work
- Methodology has been implied to standalone physical property models (e.g. viscosity, density, surface tension)
  - Thermodynamic framework considered to be most essential physical property

# Deterministic and Stochastic Modeling

## Deterministic Modeling

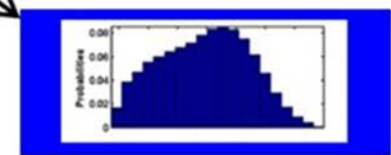
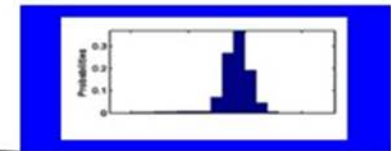
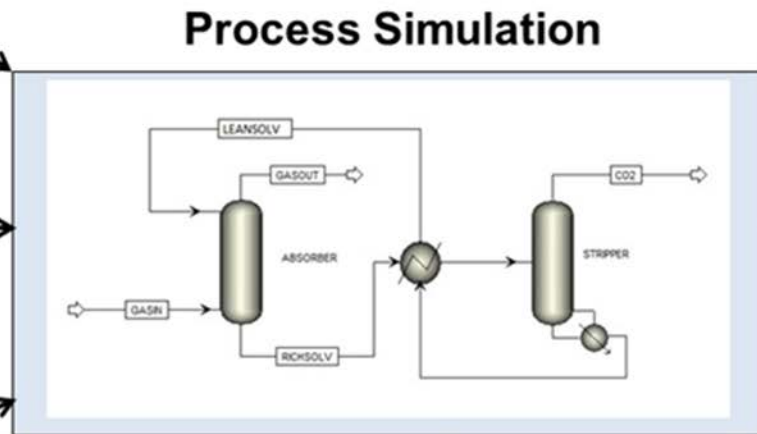
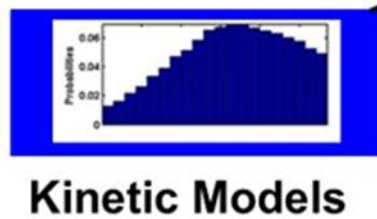
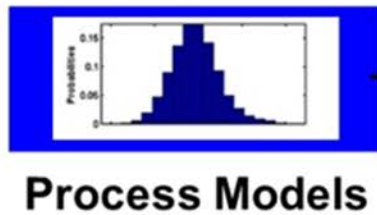
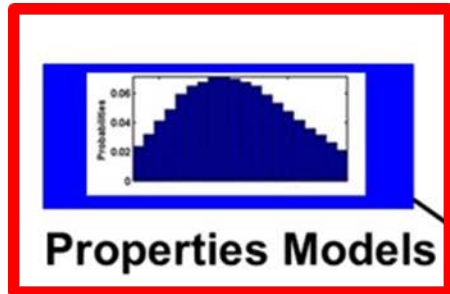
- Single value of
  - Predictor variables
  - Model parameters
  - Output variables
- Parameters calibrated from experiments
  - Best fit methods

## Stochastic Modeling

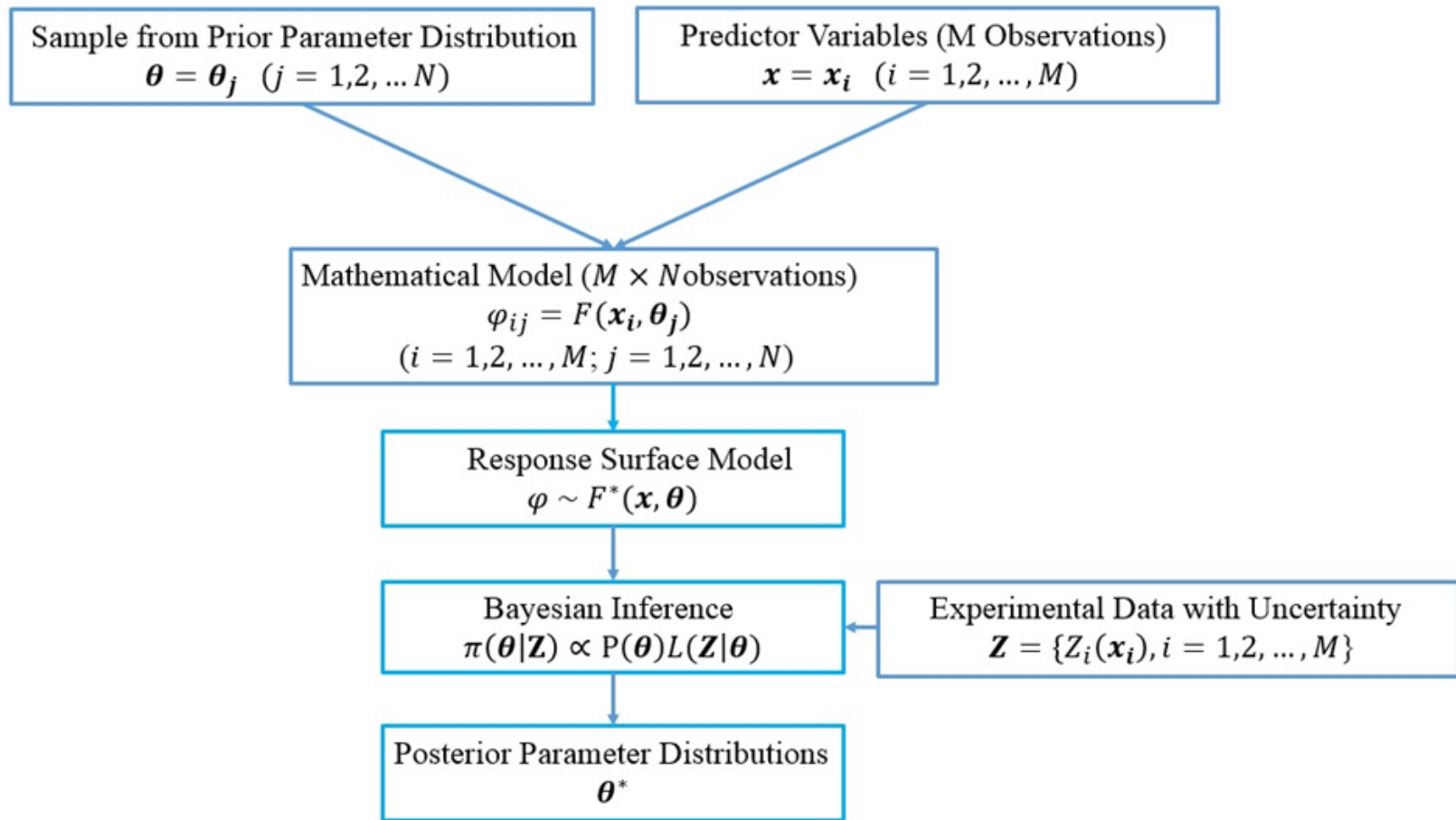
- Model inputs and outputs are probability distributions
- Rationale
  - Variability of measurements (input uncertainty)
  - Physical properties
    - Experimental data uncertainty
    - Model uncertainty

# Overall Approach

Focus of this work:  
e-NRTL thermodynamic  
framework: VLE, heat capacity,  
heat of absorption



# Stochastic Modeling Methodology

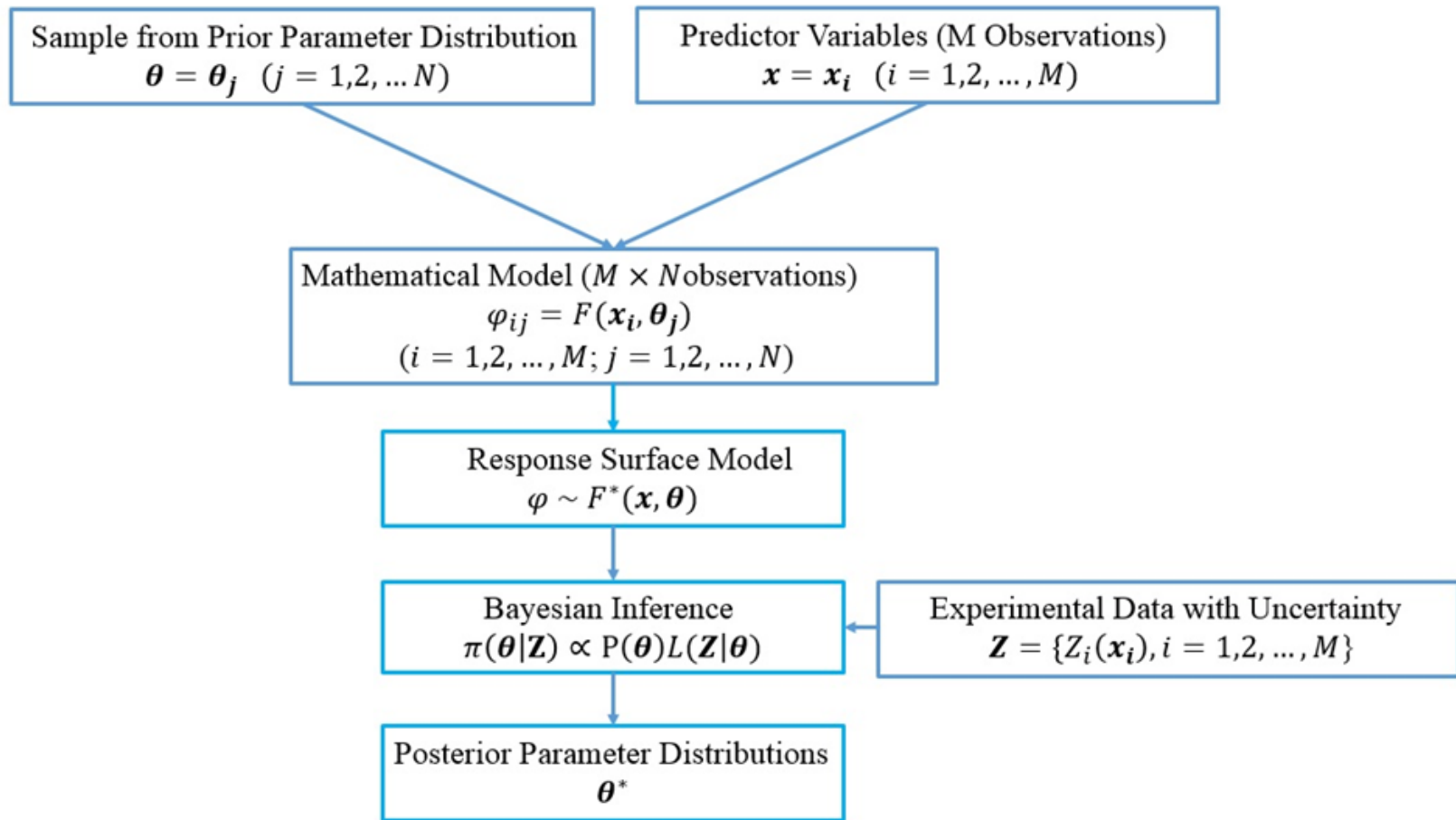


# Response Surface Analysis

- Computationally inexpensive surrogate models
- Method
  - Multivariate Adaptive Regression Splines (MARS)
- Procedure
  - Generate input sample
  - Collect output from model simulation
  - Select a response surface scheme and perform fitting
  - Validate the response surface

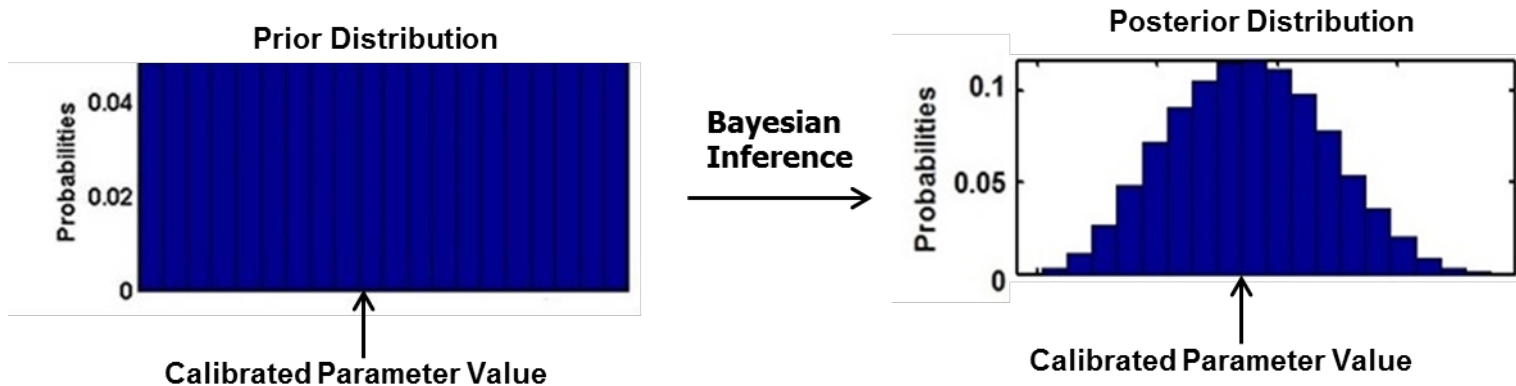


# Stochastic Modeling Methodology

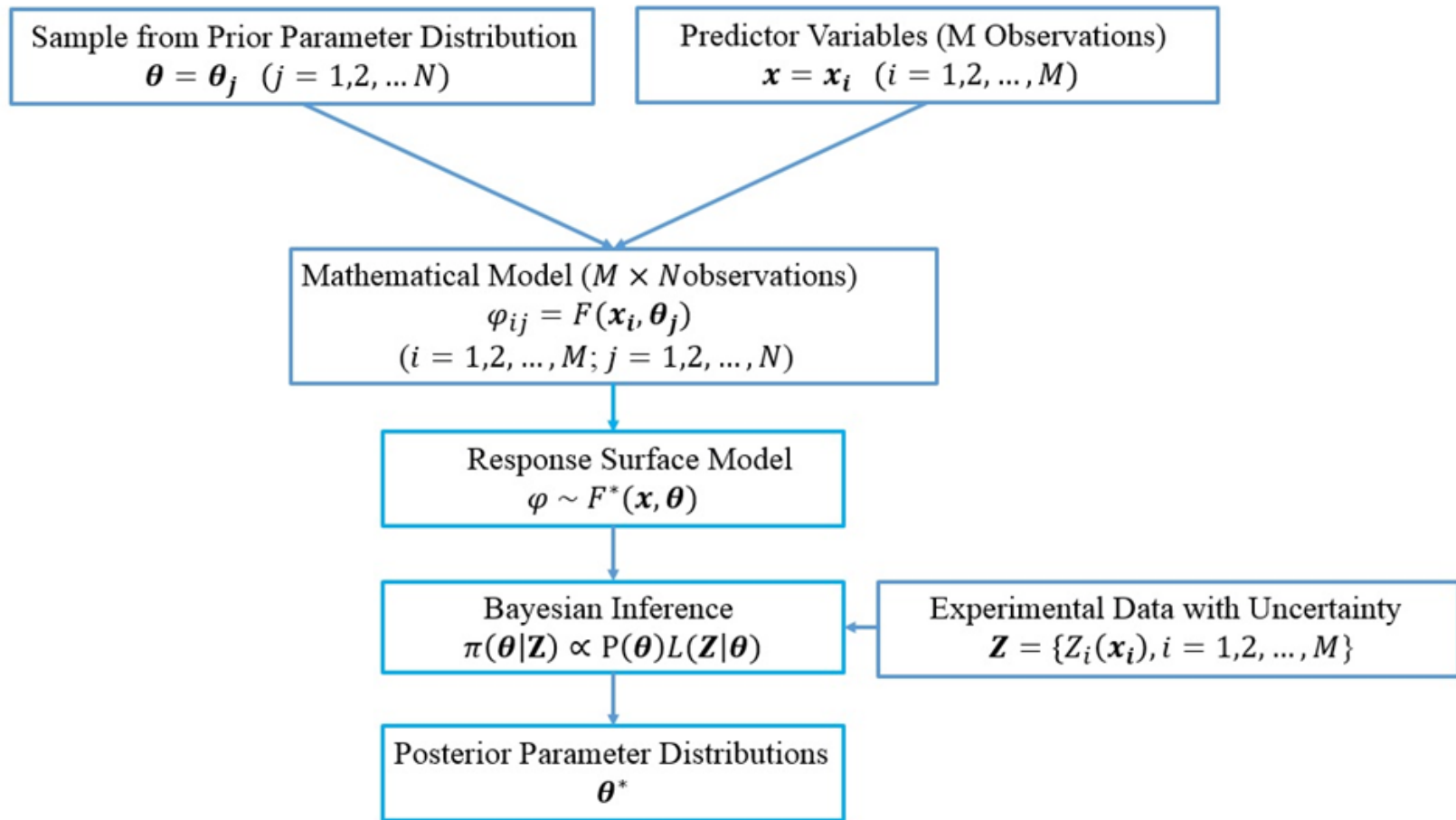


# Bayesian Inference

- Bayesian inference seeks to update prior beliefs of parameter uncertainties in view of data
  - Idea: scan intelligently the prior parameter uncertainty space to identify values that match well with available data
  - Algorithm: Markov Chain Monte Carlo (MCMC) method using Gibbs sampling

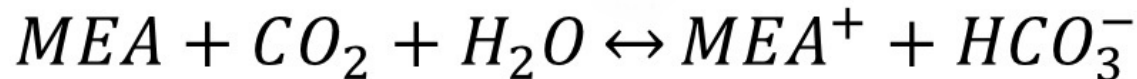


# Stochastic Modeling Methodology



# Phoenix Model Overview

- Developed by Rochelle group at University of Texas-Austin<sup>1</sup>
- Liquid phase modeled by e-NRTL model
- Vapor phase modeled by Redlich-Kwong equation of state
- Simplified electrolyte speciation<sup>2</sup>



- Highly non-ideal solution

1. Jorge Mario Plaza, Ph.D. Dissertation, UT Austin, May 2012  
2. Marcus Hilliard, Ph.D. Dissertation, UT Austin, May 2008

# Phoenix Model Overview

- 41 individual parameters regressed
  - Standard Gibbs Free Energy/ Enthalpy of Formation for Electrolytes
  - Ideal Gas and Electrolyte Component Heat Capacity Parameters
  - Henry's Constant Parameters
  - Molecule-Molecule Binary Parameters
  - Electrolyte-Molecule Pair Parameters
  - Electrolyte-Electrolyte Pair Parameters
- Data types considered
  - Vapor liquid equilibrium
  - Heat capacity
  - Heat of absorption

# Thermodynamic Relationships

Equilibrium condition for system  $\hat{\phi}_i y_i P = \gamma_i^* x_i H_i$

$$\ln(\gamma_i) = \frac{1}{RT} \left. \frac{\partial(nG^{ex})}{\partial n_i} \right|_{T,P,n_{j \neq i}} \quad G^{ex} = G_{PDH}^{ex} + G_{Born}^{ex} + G_{LC}^{ex}$$

$$\Delta H_{abs} = R \left. \frac{\partial \ln(\hat{f}_{CO_2})}{\partial (1/T)} \right|_{P,x_i}$$

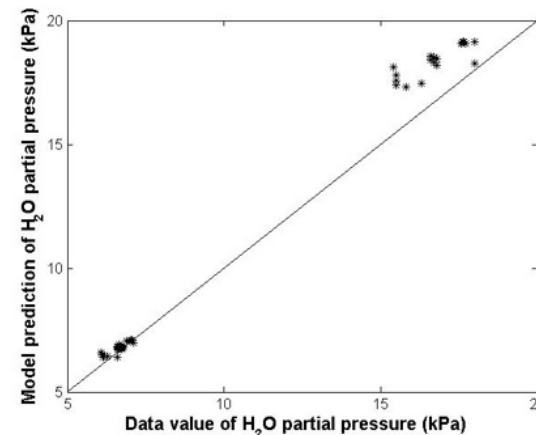
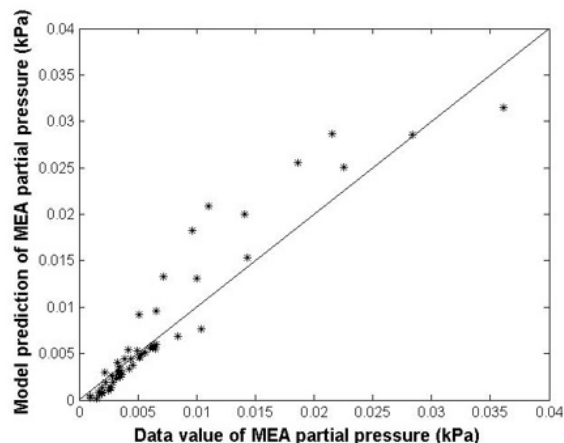
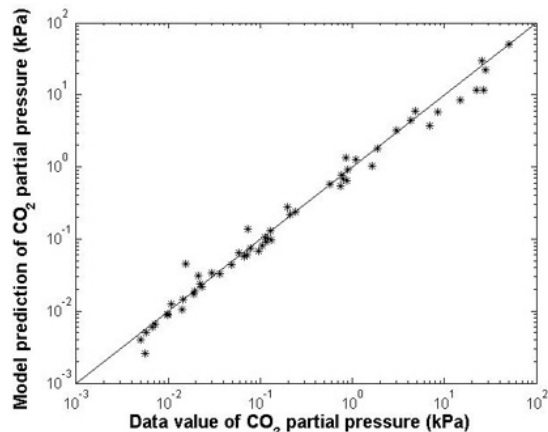
$$\frac{-H^{ex}}{T^2} = \left. \frac{\partial(G^{ex}/T)}{\partial T} \right|_{P,x_i}$$

Interaction parameters embedded in local contribution of excess Gibbs energy

Heat capacity parameters used in enthalpy calculation

**Need to regress data types simultaneously to maintain thermodynamic consistency**

# VLE Example: Phoenix Model Comparison



## Data Predictor Variable Ranges

3.5 and 7 m MEA solutions

Loading = 0.1-0.6 mol CO<sub>2</sub>/ mol MEA

Temperature = 40°C and 60°C

Data from: Marcus Hilliard, Ph.D. Dissertation, UT Austin, May 2008

	Average	Standard Deviation
$P_{CO_2}$	22.46 %	29.43 %
$P_{MEA}$	31.05 %	25.69 %
$P_{H_2O}$	4.80 %	4.37 %

# VLE Example, Continued

- Performed Bayesian inference with prior distributions of  $\pm 30\%$  Phoenix model values for 11 molecule-molecule binary interaction parameters

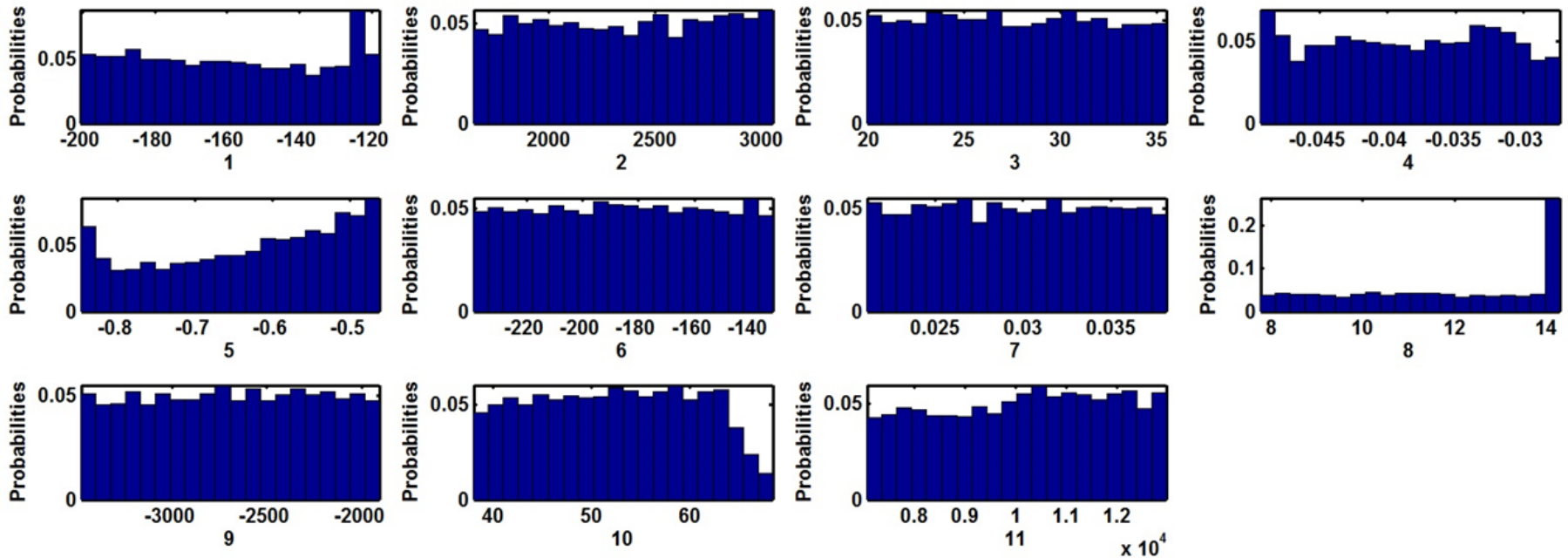
$$\tau_{mm'} = A_{mm'} + \frac{B_{mm'}}{T} + E_{mm'} \ln(T) + F_{mm'} T$$

Equation embedded in local contribution of excess Gibbs free energy equation

Parameter Number	Parameter Identity
1	$A_{H_2O-MEA}$
2	$B_{H_2O-MEA}$
3	$E_{H_2O-MEA}$
4	$F_{H_2O-MEA}$
5	$A_{MEA-H_2O}$
6	$B_{MEA-H_2O}$
7	$E_{MEA-H_2O}$
8	$A_{CO_2-MEA}$
9	$B_{CO_2-MEA}$
10	$A_{MEA-CO_2}$
11	$B_{MEA-CO_2}$



# VLE Example UQ Results



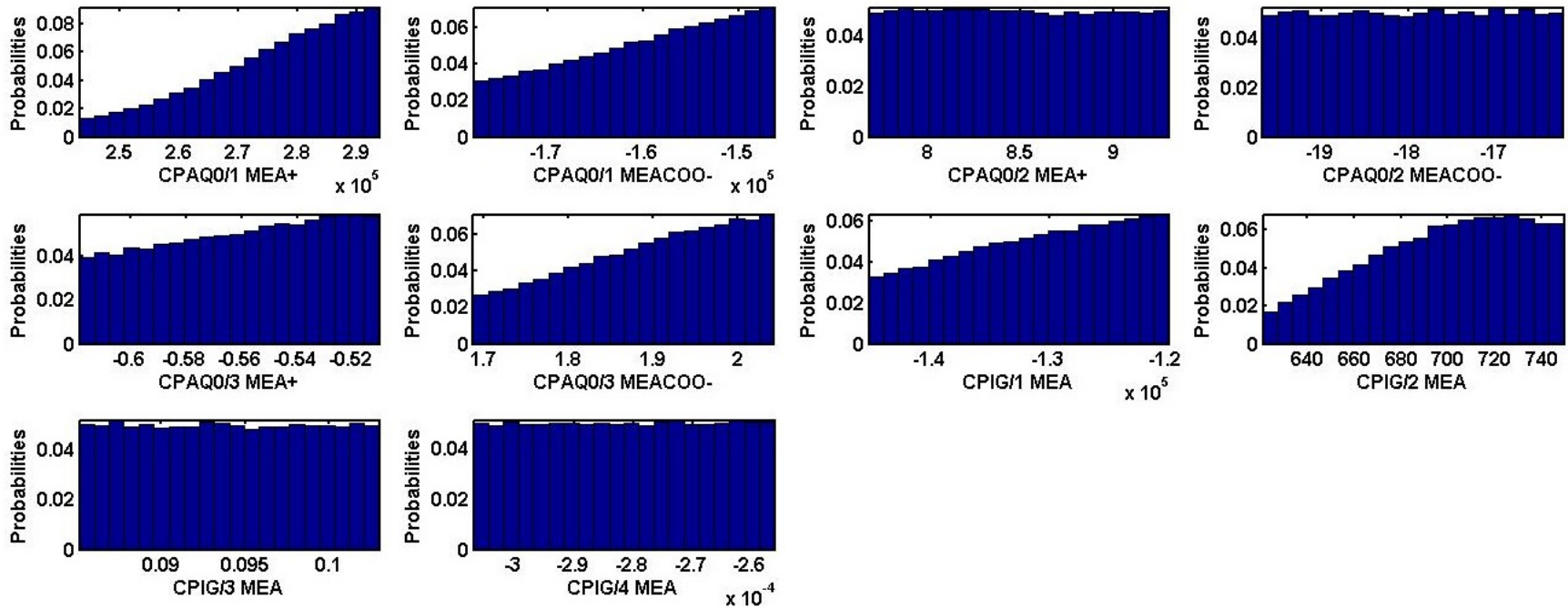
# Example: Heat Capacity

- Performed Bayesian inference with prior distributions of  $\pm 10\%$  of parameters
  - 3 parameters for CPAQ0 model of MEA+
  - 3 parameters for CPAQ0 model of MEACOO-
  - 4 parameters for CPIG model of MEA
- Used data from Hilliard and Weiland
- Heat capacity polynomial forms:

$$C_{p,i}^{ig} = C_{1i} + C_{2i}T + C_{3i}T^2 + C_{4i}T^3 + C_{5i}T^4 + C_{6i}T^5$$

$$C_{p,k}^{\infty} = C_{1i} + C_{2i}T + C_{3i}T^2 + \frac{C_{4i}}{T} + \frac{C_{5i}}{T^2} + \frac{C_{6i}}{\sqrt{T}}$$

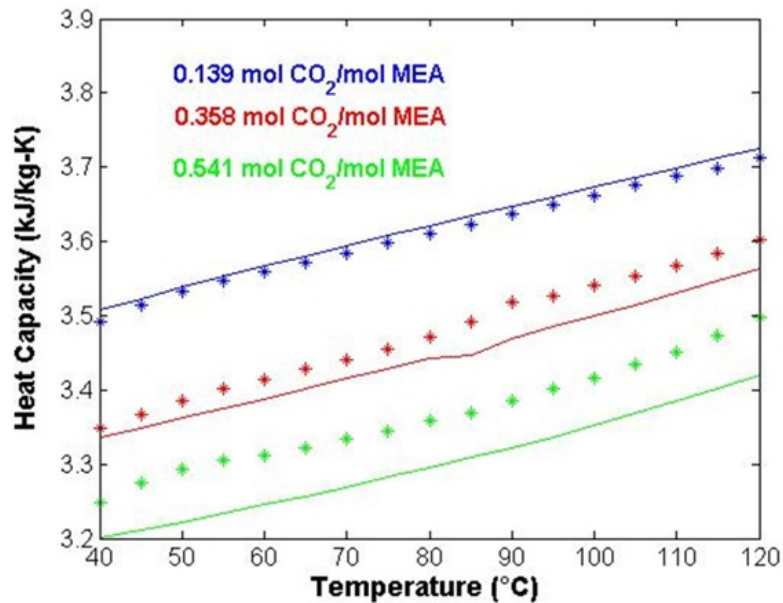
# Heat Capacity UQ Results



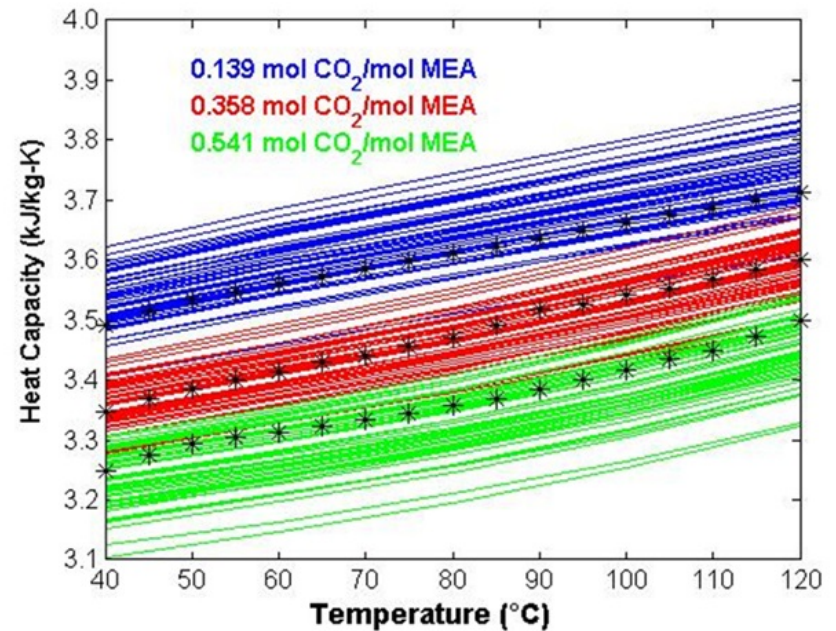
# Heat Capacity: Deterministic and Stochastic Models

7 m aqueous MEA solutions

Phoenix Model



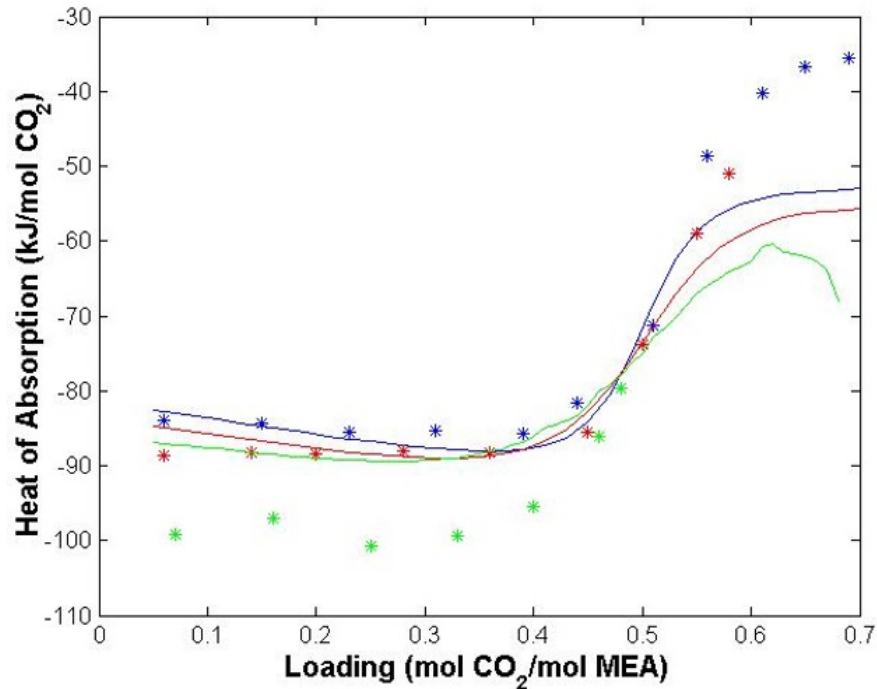
Posterior Distribution of Sample Size 50



Experimental data from: Marcus Hilliard, Ph.D. Dissertation, UT Austin, May 2008

# Heat of Absorption

Phoenix Model Comparison (parameters not regressed to match data)



$$\Delta H_{abs} = R \left. \frac{\partial \ln(\hat{f}_{CO_2})}{\partial (1/T)} \right|_{P, x_i}$$

Data from Kim et al., GHGT-12

# Future Work

- Complete physical property models uncertainty quantification
  - e-NRTL thermodynamic framework: VLE, heat capacity, heat of absorption
  - Diffusivity
- Propagate all stochastic models (e.g. physical properties, kinetics, mass transfer and hydraulics) through process simulation
- Validation of overall stochastic model with process data
  - Steady state data from UT Austin pilot plant
  - Steady state and dynamic data from NCCC

# Thank you!

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