

Simplified Predictive Models for CO₂ Sequestration Performance Assessment

DE-FE-0009051

Srikanta Mishra

Battelle Memorial Institute

**Priya Ravi Ganesh,
Jared Schuetter, Doug Mooney**
Battelle Memorial Institute

**Louis Durlinsky
Jincong He**
Stanford University

U.S. Department of Energy
National Energy Technology Laboratory
Carbon Storage R&D Project Review Meeting
Developing the Technologies and
Infrastructure for CCS
August 20-22, 2013

Presentation Outline

- Benefit to the Program / Stakeholders
- Project Overview
- Technical Status
 - Simplified physics based modeling
 - Statistical learning based modeling
 - Reduced order method based modeling
- Accomplishments to Date
- Summary

Benefit to the Program

- Research will develop and validate a portfolio of simplified modeling approaches to predict the extent of CO₂ plume migration, pressure impact and brine movement for a semi-confined system with vertical layering
- These approaches will improve existing simplified models in their applicability, performance and cost
- The technology developed in this project supports the following programmatic goals: (1) estimating CO₂ storage capacity in geologic formations; (2) demonstrating that 99 percent of injected CO₂ remains in the injection zone(s); and (3) improving efficiency of storage operations

Benefit to Stakeholders

- Provide ***project developers*** with simple tools to screen sites and estimate monitoring needs
- Provide ***regulators*** with tools to assess geological storage projects quickly without running full-scale detailed numerical simulations
- Enable ***risk assessors*** to utilize robust, yet simple to implement, reservoir performance models
- Allow ***modelers*** to efficiently analyze various CO₂ injection plans for optimal well design/placement

Project Overview

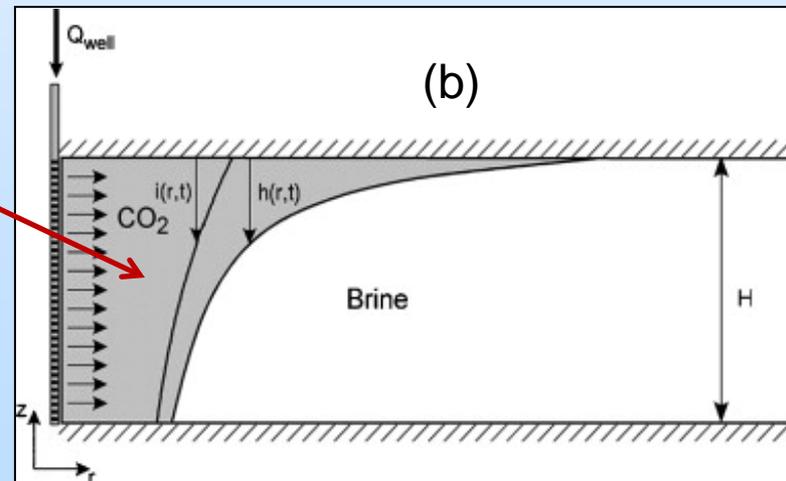
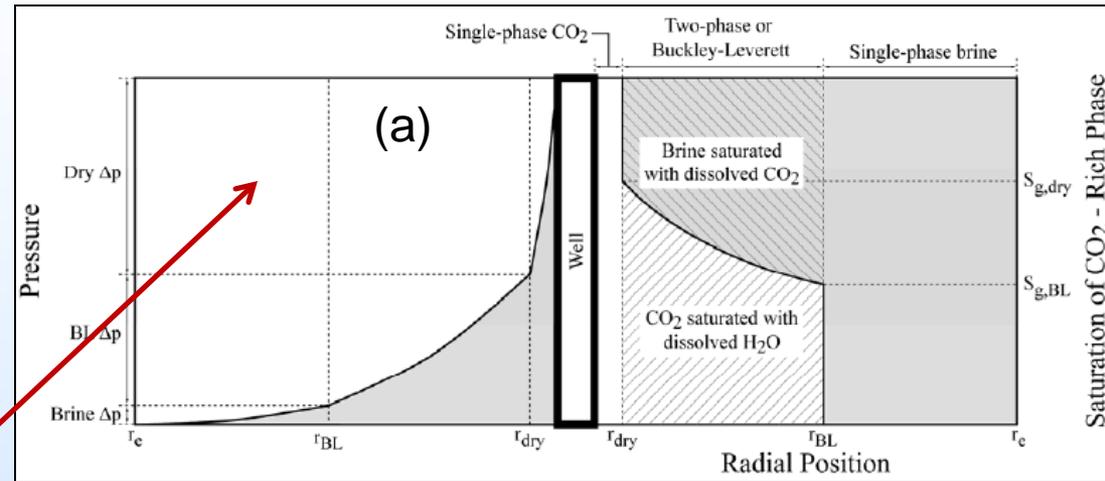
Goals and Objectives

- **Objective** ⇒ Develop and validate a portfolio of simplified modeling approaches for CO₂ sequestration in deep saline formations
 - **Simplified physics-based modeling** - where only the most relevant processes are modeled
 - **Statistical-learning based modeling** - where the simulator is replaced with a “response surface”
 - **Reduced-order method based modeling** - where mathematical approximations reduce computational burden
 - **Uncertainty and sensitivity analysis** – to validate the simplified modeling approaches for probabilistic applications

Simplified Physics Based Models

Background

- Useful alternative to simulators if “macro” behavior is of interest
- Analytical models of radial injection of supercritical CO₂ into confined aquifers
 - (a) Fractional flow model (Burton et al., 2008; Oruganti & Mishra; 2013)
 - (b) Sharp interface model (Nordbotten & Celia, 2008)
- Require extension for semi-confined systems with vertical layering (based on detailed simulations)

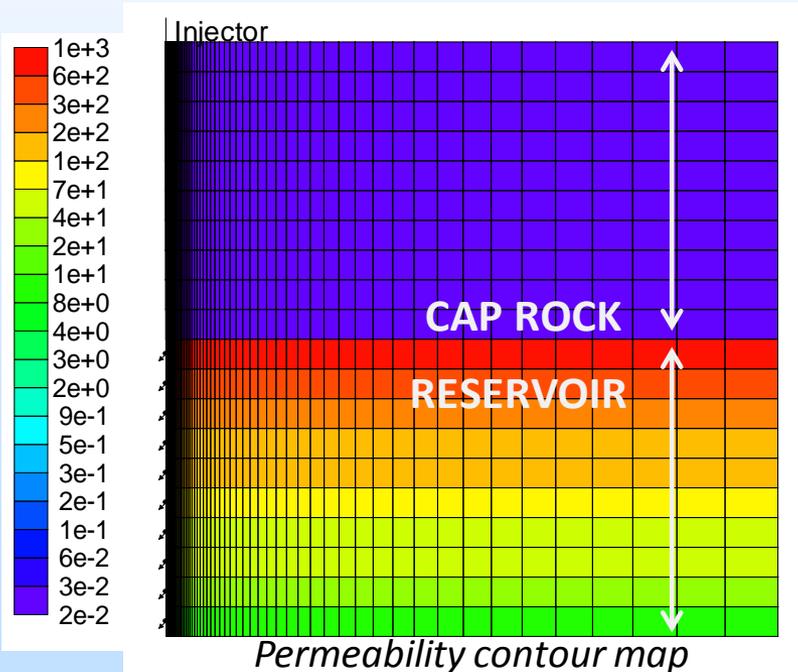


Simplified Physics Based Models

Approach (using GEM)

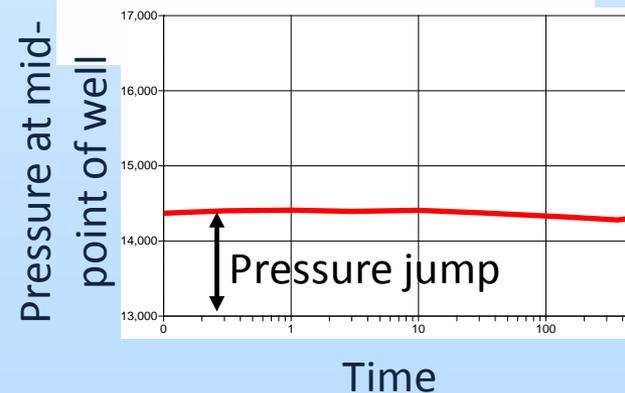
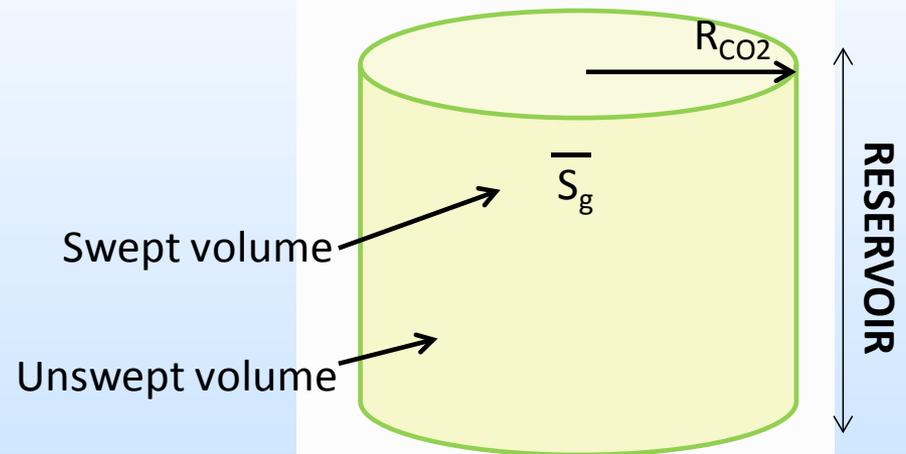
INPUT VARIABLES

CAP ROCK PROPERTIES:
 $\phi, h, \langle K \rangle, P_c$



RESERVOIR ROCK PROPERTIES:
 $\phi, h, \langle K \rangle, K_v/k_h, K_{rel}$

PERFORMANCE METRICS

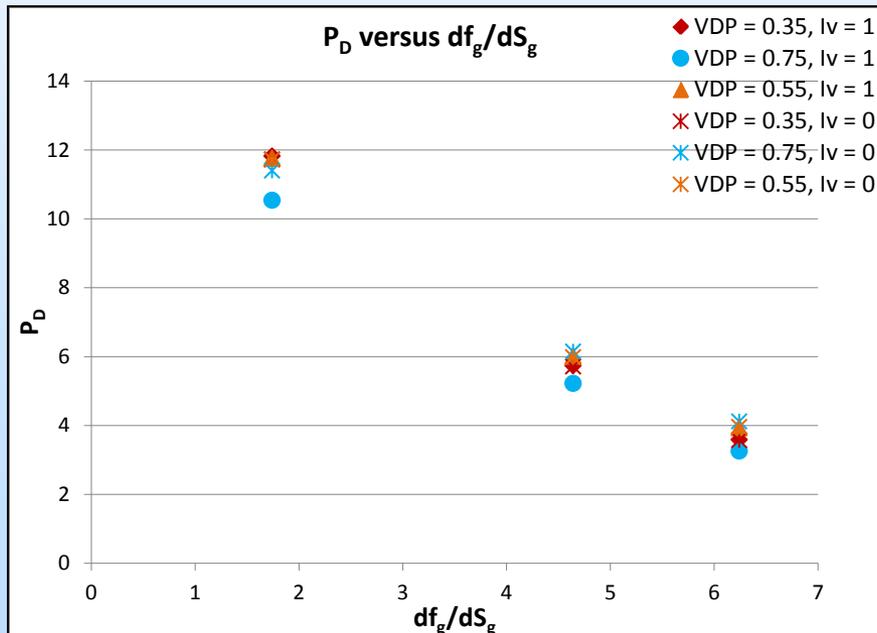


Simplified Physics Based Models

Dimensionless Injectivity

$$\Delta P_{tot} = \frac{q_{CO_2}}{2\pi kH} \left[\frac{\ln(r_{dry} / r_w)}{1 / \mu_g} + \frac{\ln(r_{BL} / r_{dry})}{M_{BL}} + \frac{\ln(r_e / r_{BL})}{1 / \mu_w} \right]$$

$$P_{D, jump} = \frac{2\pi kH}{q\mu_w} \Delta P_{jump}$$



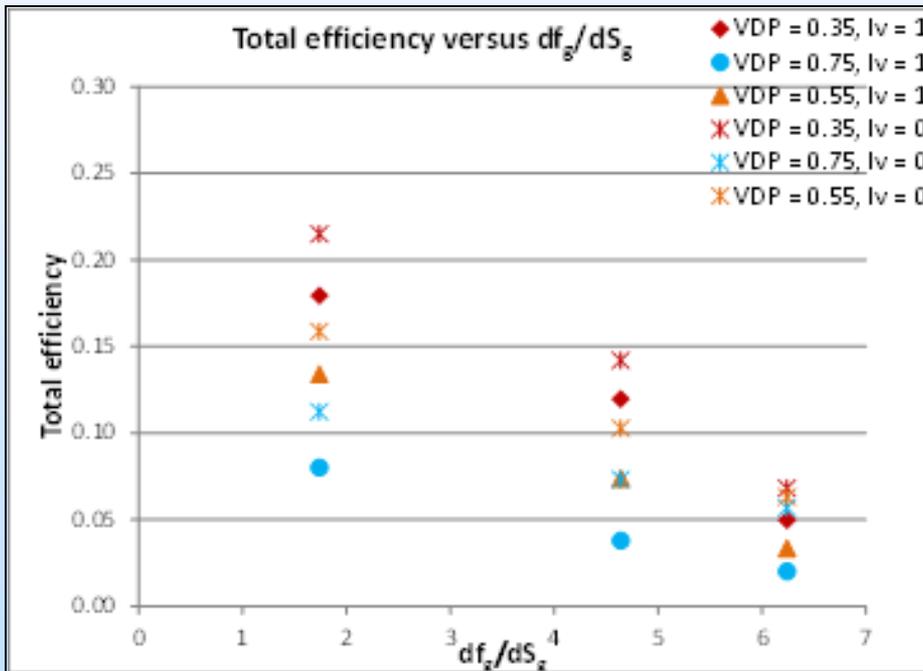
If P_D can be predicted,
then q v/s ΔP relationship can
be established

Next steps \Rightarrow Fitting data
 $P_D = f\{df_g/dS_g; V_{DP}, I_v\}$

Simplified Physics Based Models

Sweep Efficiency

$$R_{CO_2}^2 = \frac{Q}{\pi\phi H \bar{S}_g E_v} = \frac{Q}{\pi\phi H E_s}$$



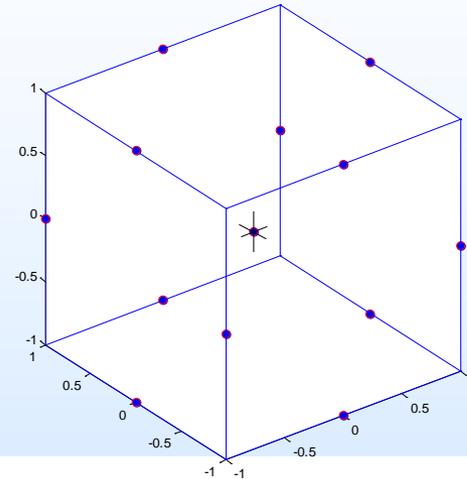
If E_s can be predicted, then R_{CO_2} can be estimated

Next steps \Rightarrow Fitting data
 $E_s = f\{df_g/dS_g; V_{DP}, I_v, N_G\}$

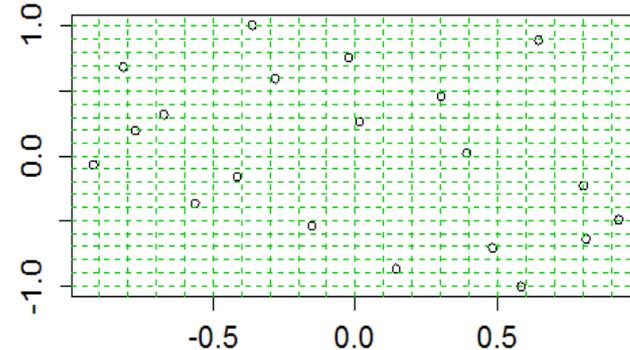
Statistical Learning Based Models

Background

- **Goal** \Rightarrow replace physics-based model with statistical equivalent
- **Experimental design** \Rightarrow selection of points in parameter space to run limited # of computer experiments
- **Response surface** \Rightarrow functional fit to input-output data to produce “proxy” model
- Two common options
 - **Box-Behnken** (BB) design
3-pt + quadratic response surface
 - **Latin Hypercube sampling** (LHS)
multi-point + higher-order model



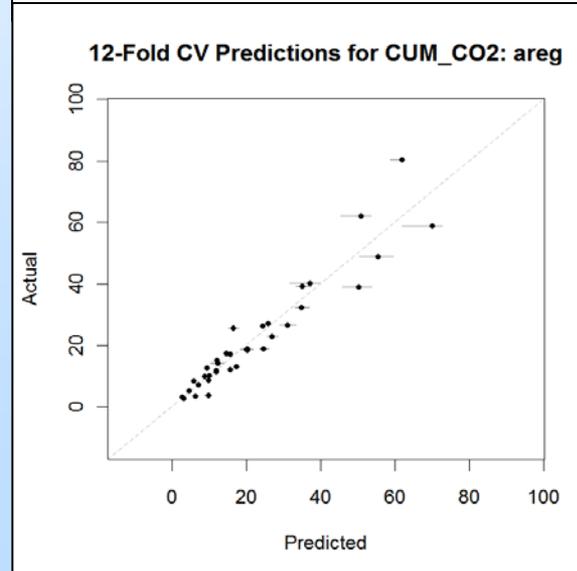
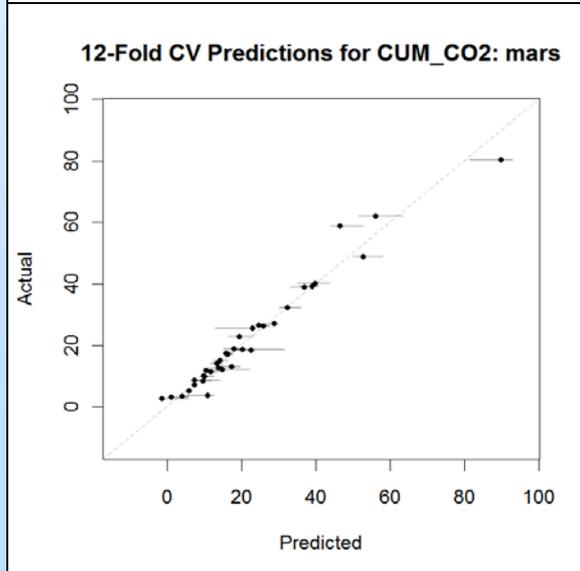
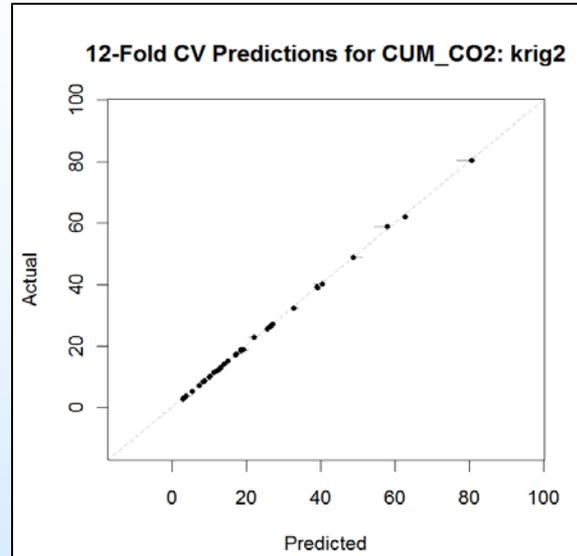
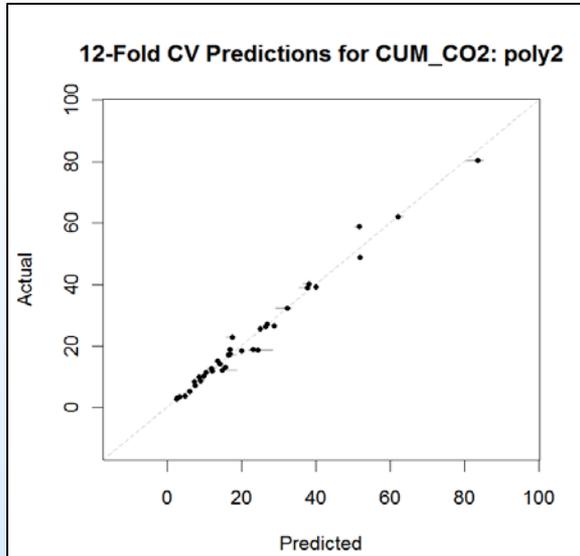
BB



LHS

Statistical Learning Based Models

Example - Metamodel Fits

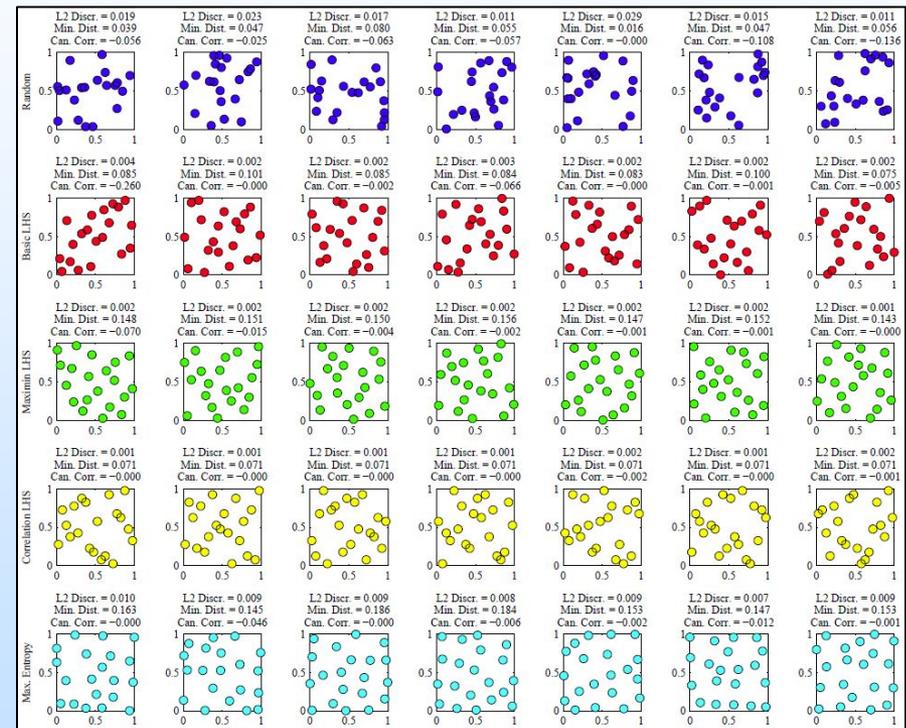
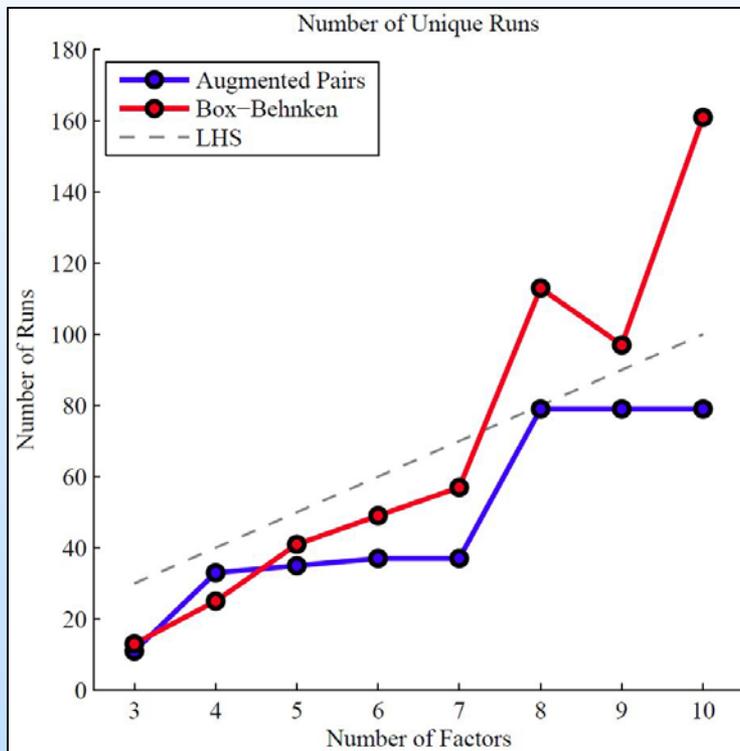


- Data from 2-D STOMP simulations of CO2 injection into closed systems (Arches province)
- 36 run full-factorial design
 - 3 stratigraphic columns (injection depth)
 - 4 well patterns
 - 3 permeability groups
- Cross validation using 12 mutually exclusive subsets (33 training + 3 test data points) with 100 replicates
- Similar results for CO2_R and PCT_CO2

Statistical Learning Based Models

Generation of Experimental Designs

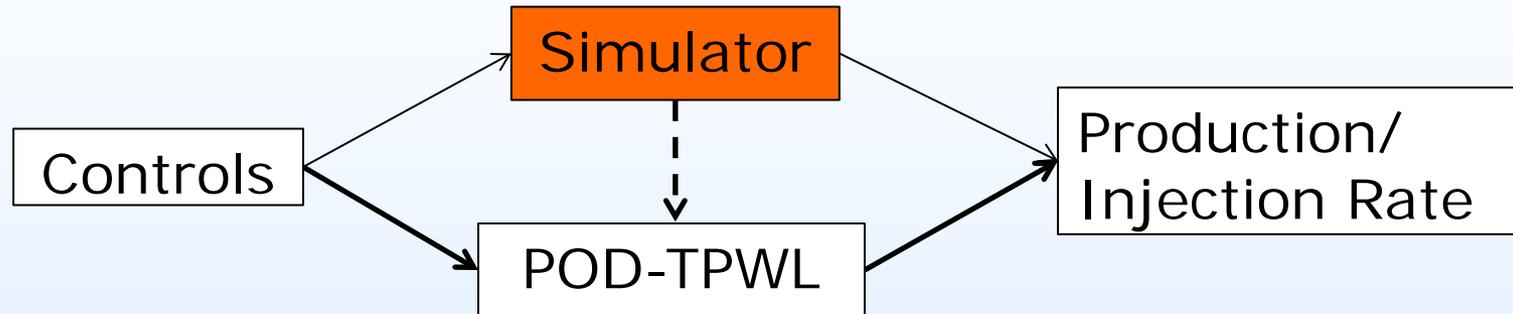
Box-Behnken Alternative



Alternative Space-Filling Designs

Reduced Order Method Based Models

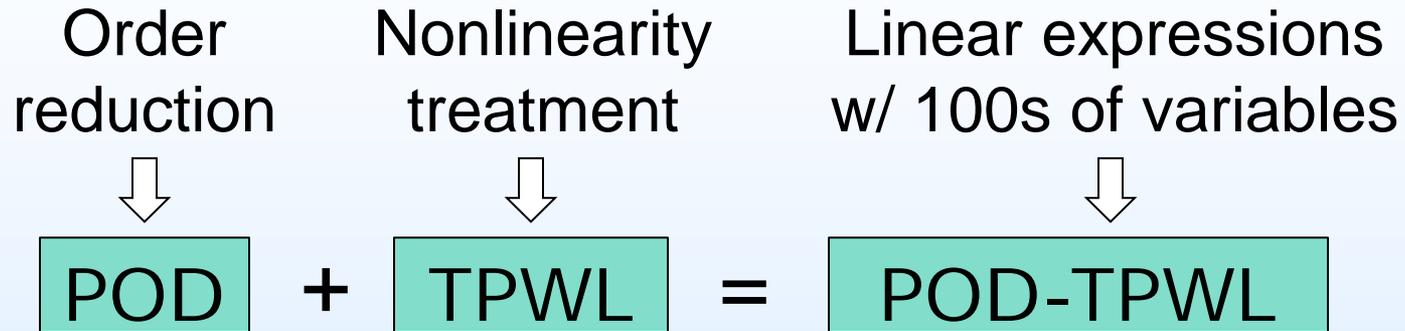
Background (1)



- Proper Orthogonal Decomposition (POD)
 - Represent high-dimensional state vectors (e.g., pressure & saturation in every grid block) with small number of variables by feature extraction
- Trajectory Piecewise Linearization (TPWL)
 - Predict results for new simulations by linearizing around previous (training) simulations

Reduced Order Method Based Models

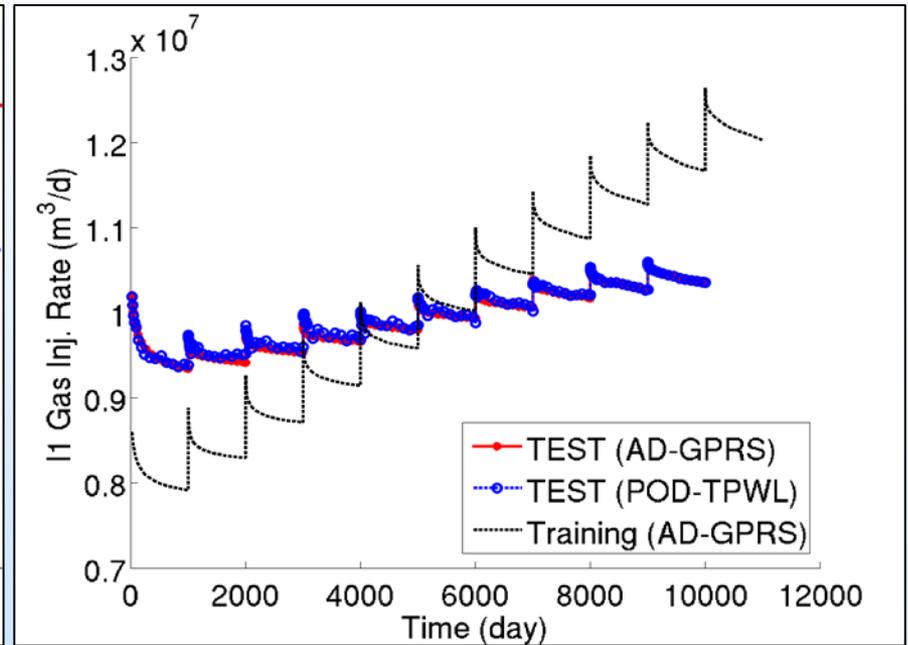
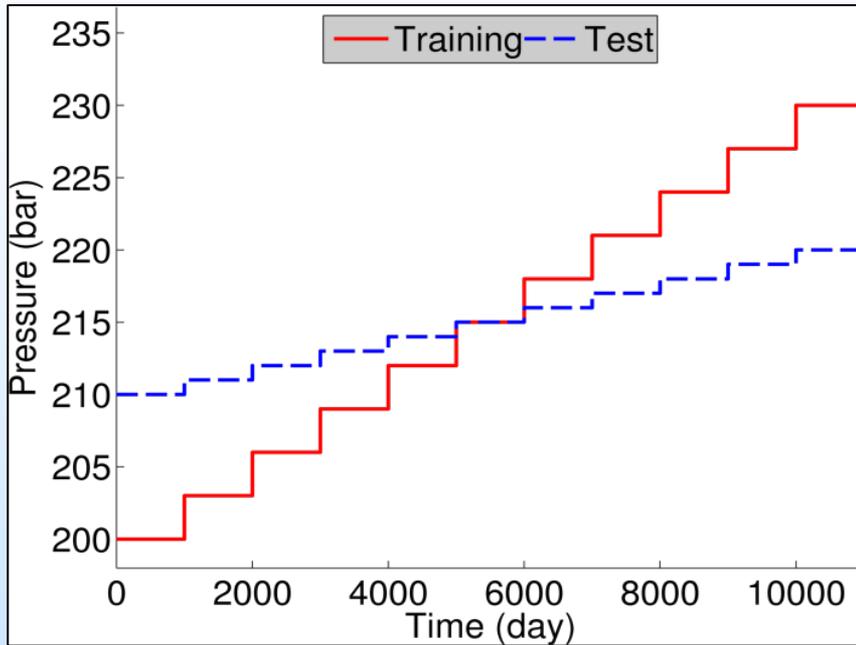
Background (2)



- Retain the physics of the original problem
- Overhead is required to build the POD-TPWL model
- Evaluation of POD-TPWL model takes only seconds
- Applied previously to oil-water problems for optimization and history matching (Cardoso and Durlofsky 2010, 2011; He et al. 2011, 2013)

Reduced Order Method Based Models

Example – POD-TPWL Performance



	AD-GPRS	POD-TPWL Construction	POD-TPWL (Test)
Run Time	~120s	~360s	~2s

Accomplishments to Date

SPBM

- Completed sensitivity analyses to identify factors influencing reservoir/caprock pressure buildup and CO₂ plume migration
- Identified possible predictive model functional forms for dimensionless injectivity and CO₂ storage efficiency

SLBM

- Completed evaluation of metamodeling techniques (2nd order polynomial, kriging, MARS, ACE)
- Completed Box-Behnken design based simulations for generating response surface based simplified models

ROMBM

- Investigated applicability of POD-TPWL for CO₂ injection into saline aquifers using a compositional simulator
- Evaluated different constraint reduction approaches

Summary

SPBM

- Developed insights into two-phase region injectivity and sweep based on detailed simulations
- Next FY's work will focus on insights for pressure buildup and developing predictive models

SLBM

- Evaluated metamodeling techniques and approaches for generating experimental designs
- Next FY's work will focus on fitting metamodels to BB and LHS simulations and comparing their predictions

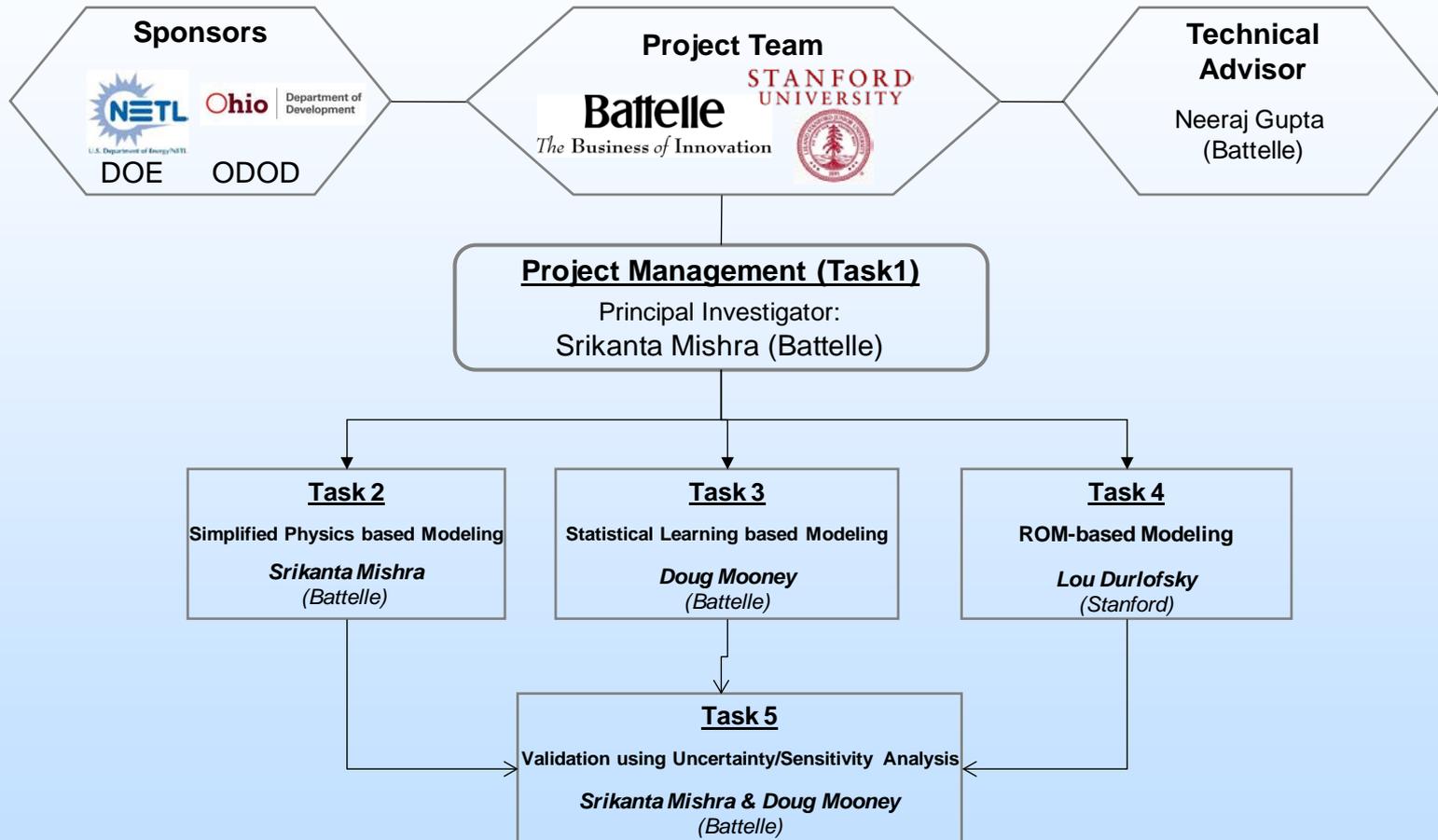
ROMBM

- Implemented POD-TPWL for saline aquifer CO₂ injection
- Next FY's work will focus on improving accuracy, stability and robustness of selected POD-TPWL schemes

Appendix

These slides will not be discussed during the presentation, **but are mandatory**

Organization Chart



Project Manager – Michael McMillian (DOE)

Bibliography

- Journal, multiple authors:
 - Schuetter, J., Mishra, S. and Mooney, D., 2013, Evaluation of metamodeling techniques for CO₂ geologic sequestration. Computers and Geoscience (to be submitted).
 - Ravi Ganesh, P. and Mishra, S., 2013, Simplified predictive modeling of CO₂ geologic sequestration in saline formations: insights into key parameters governing buoyant plume migration and pressure propagation. SPE Reservoir Evaluation and Engineering (to be submitted).