



Risk Assessment for CO₂ Sequestration-Uncertainty Quantification based on Surrogate Models of Detailed Simulations

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Modeling CO₂ Underground Plume



For
$$\alpha = CO_2$$
, brine

$$\frac{\partial \phi_{\alpha} S_{\alpha}}{\partial t} + \nabla \cdot (\rho_{\alpha} \mathbf{v}_{\alpha}) = V_{\alpha} \rho_{\alpha}, \qquad \mathbf{v}_{\alpha} = -\frac{K \mathbf{k}_{\alpha}}{\mu_{\alpha}} (\nabla p_{\alpha} + \rho_{\alpha} g \nabla z)$$
Mass balance
Darcy's law

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Uncertainty Analysis Options

- Numerical model + Monte Carlo simulation
- Stochastic response surface methods
 - Surrogate model
 - Approximate the output of the original model by polynomial functions of the uncertain parameters
 - Monte Carlo simulation with surrogate model

The primary goal of this work is to provide an assessment of surrogate-based uncertainty analysis for CO₂ injection into a saline aquifer

Polynomial Chaos Expansion (PCE)

A physical model

 $\boldsymbol{Y} = M(\boldsymbol{x})$

 $\boldsymbol{x} = \{x_1, ..., x_M\}^T \in \mathbb{R}^M, M \ge 1$ porosity, permeability, etc

 $\boldsymbol{Y} = \{y_1, ..., y_N\}^T \in \mathbb{R}^N, N \ge 1$ CO₂ mass, CO₂ plume dynamic, etc

Random $x \rightarrow$ random model response y

Assuming finite variance, chaos representation

$$y = M(\mathbf{x}) = \alpha_0 + \alpha_1 B_1(\mathbf{x}) + \alpha_2 B_2(\mathbf{x}) + \alpha_3 B_3(\mathbf{x}) + \dots$$

 $\{B_1, B_2, B_3, ...\}$: orthogonal polynomial basis functions for \boldsymbol{x}

Orthogonal Polynomial Basis

$^\circ$ Orthogonal polynomials for a <u>single</u> random x

- $\varphi_d(x) = x^d + \text{lower-degree terms}, \quad d = 0, 1, 2, ...$ f(x): probability density function $\int_{\Omega} \varphi_d(x) \varphi_c(x) f(x) dx = 0, d \neq c$ <u>Multivariate polynomial basis for $x = \{x_1, ..., x_M\}^T \in \mathbb{R}^M, M \geq 2$ </u>
- <u>Multivariate</u> polynomial basis for $oldsymbol{x} = \{x_1, ..., x_M\}^{r} \in \mathbb{R}^{m}$
 - Independent $B_d(x_1, ..., x_M) = \prod_{i=1}^M \varphi_{d_i}(x_i), \quad \sum_{i=1}^M d_i = d$
 - Dependent: Nataf Transformation

 $\Phi(z_i) = F(x_i) \quad \text{correlated variables} \rightarrow \text{correlated standard normals}$ $z = L \boldsymbol{\xi} \quad \text{correlated normals} \rightarrow \text{uncorrelated standard normals}$ $y = M(\boldsymbol{\xi})$

Coefficient Estimation

$$y = M_d(\boldsymbol{x}) = \alpha_0 + B_1 \alpha_1 + \dots + B_d \alpha_d$$

Regression

 $oldsymbol{X} = \{oldsymbol{x}^1, ..., oldsymbol{x}^{N_p}\}$: a set of N_p realizations of random input vectors $oldsymbol{y} = \{oldsymbol{y}^1, ..., oldsymbol{y}^{N_p}\}^T = \{oldsymbol{y}^i = M_d(oldsymbol{x}^i), i = 1, ..., N_p\}^T$ $oldsymbol{B} oldsymbol{lpha} = oldsymbol{y}$ $oldsymbol{lpha} = oldsymbol{y}$ $oldsymbol{lpha} = (oldsymbol{B}^T oldsymbol{B})^{-1} oldsymbol{B}^T oldsymbol{y}$

Number of points to choose:

 $N_t = \frac{(M+d)!}{M!d!}$ d: degree of expansion, M: inputs

M	<i>d</i> = 1	<i>d</i> = 2	 <i>d</i> = 6
1	1	3	7
5	6	21	462
10	11	66	<u>8008</u>

Stepwise PCE Approximation



S. Weisberg, Applied Linear Regression, 3rd edition, 2005

Assessment of PCE approximation

Empirical error

$$R^{2} = 1 - \frac{\frac{1}{N_{p}} \sum_{i=1}^{N_{p}} (y^{i} - M_{d}(\boldsymbol{x}^{i})^{2})}{\sigma^{2}(\boldsymbol{y})}$$

 $R^2 \rightarrow 1$ as N_t increases \rightarrow overfitting

Leave-one-out cross validation



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Case Study

CO₂ injection into a deep saline aquifer Simulated using TOUGH2 developed by LBNL since 1980

output = M (porosity, permeability)



Specify Input Random Variables

National Petroleum Council Public Database

Non-standard marginal distributions



Derive Orthogonal Polynomial Basis

Hermite polynomials for a standard normal random variable

$$\varphi_0(\xi) = 1$$

$$\varphi_1(\xi) = \xi$$

$$\varphi_2(\xi) = \xi^2 - 1$$

$$\varphi_3(\xi) = \xi^3 - 3\xi$$

$$\varphi_{d+1} = \xi\varphi_d - d\varphi_{d-1}$$

• Basis for the two-dimensional independent input vector (ξ_1, ξ_2)

$$B_{0}(\boldsymbol{\xi}) = \varphi_{0}(\xi_{1})\varphi_{0}(\xi_{2}) = 1$$

$$B_{1}(\boldsymbol{\xi}) = \varphi_{1}(\xi_{1})\varphi_{0}(\xi_{2}) = \xi_{1}$$

$$B_{1}(\boldsymbol{\xi}) = \varphi_{0}(\xi_{1})\varphi_{1}(\xi_{2}) = \xi_{2}$$

$$B_{2}(\boldsymbol{\xi}) = \varphi_{2}(\xi_{1})\varphi_{0}(\xi_{2}) = \xi_{1}^{2} - 1$$

$$B_{2}(\boldsymbol{\xi}) = \varphi_{1}(\xi_{1})\varphi_{1}(\xi_{2}) = \xi_{1}\xi_{2}$$

$$B_{2}(\boldsymbol{\xi}) = \varphi_{0}(\xi_{1})\varphi_{2}(\xi_{2}) = \xi_{2}^{2} - 1$$

Build PCE Model

Select an experimental design ξ (Latin Hypercube Sampling)



 ξ_2

Build PCE Model

* Select an experimental design ξ (Latin Hypercube Sampling)



ξ_2

Reverse of Nataf transformation

$$\boldsymbol{z} = L\boldsymbol{\xi} \qquad \qquad \boldsymbol{x}_i = F^{-1}(\Phi(\boldsymbol{z}_i))$$

Model output evaluations

Stepwise regression for coefficients and degree

PCE Model Example 1



PCE Model Example 2



Use PCEs for Uncertainty Analysis



Correlated Sampling Using Copulas



MC Simulation Result 1



MC Simulation Result 2



Pressure Map with TOUGH2



Pressure Map with PCE Model



Maximum Caprock Pressure



Gas Saturation Map with TOUGH2



Gas Saturation Map with PCE Model



Optimal Injection under Uncertainty



$$\max_{z} \quad \mathbb{E}_{\xi_1, \xi_2 \in \Omega} \left(\sum_{i=1}^{986} S_{g_i}(z, \xi_1, \xi_2) \right)$$

s.t.
$$p(z,\xi_1,\xi_2) \le p_{\text{limit}}$$

Nonconvex stochastic NLP solved with BARON using scenario-based approach

Optimal injection rates under various realizations of uncertain parameters

Conclusions

Polynomial chaos expansion model was iteratively built with stepwise regression for correlated uncertain parameters

- Results obtained with PCE-based surrogate model match well the results obtained with TOUGH2
- Developed a nonconvex stochastic NLP model for finding optimal injection rate under model uncertainty

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