

Adaptive Sparse-Grid Stochastic Collocation Uncertainty Quantification Convergence for Multigroup Diffusion

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INTRODUCTION

Advanced methods in uncertainty quantification for numerical models in computational physics [1, 2] continue to gain acceptance in nuclear modeling [3, 4]. Previously, we demonstrated the efficiency of sparse-grid stochastic collocation in comparison with Monte Carlo for uncertainty quantification through convergence studies [5]. We consider an adaptive method for anisotropic sparse grid collocation and its convergence compared to previous efforts.

The physical system we consider is a two-dimensional quarter-core reactor, consisting of 5 materials distributed in 121 regions (see Fig. 1). We solve the two-group neutron diffusion criticality approximation

$$-\nabla \cdot (D_1(\bar{x}) \nabla \phi_1(\bar{x})) + (\Sigma_a^{(1)}(\bar{x}) + \Sigma_s^{(1 \rightarrow 2)}(\bar{x})) \phi_1(\bar{x}) = \frac{1}{k(\phi)} \sum_{g'=1}^2 \nu_{g'} \Sigma_f^{(g')}(\bar{x}) \phi_{g'}(\bar{x}), \quad (1)$$

$$-\nabla \cdot (D_2(\bar{x}) \nabla \phi_2(\bar{x})) + \Sigma_a^{(2)}(\bar{x}) \phi_2(\bar{x}) = \Sigma_s^{(1 \rightarrow 2)}(\bar{x}) \phi_1(\bar{x}). \quad (2)$$

We apply vacuum boundaries on the top and right, and reflecting boundaries on the bottom and left. The criticality eigenvalue and quantity of interest $k(\phi)$ is given by

$$k(\phi) = \sum_{g=1}^2 \iint_D \frac{\nu \Sigma_f^{(g)} \phi_g(\bar{x})}{(-\nabla \cdot D_g \nabla + \Sigma_r^{(g)}) \phi_g(\bar{x})} d\bar{x}. \quad (3)$$

The material properties are shown in Table I, and the domain is $[0, 200 \text{ cm}]^2$. The reference value $k=1.00007605445$.

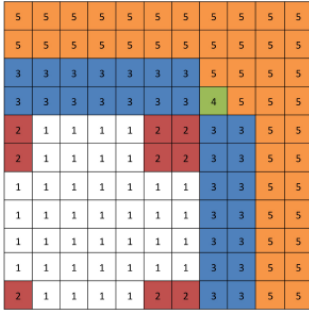


Fig. 1: Core Geometry

The material cross sections, neutron multiplication factors, and diffusion coefficients are potential uncertain input parameters. We introduce uniformly-distributed uncertainty within 5% of the reference values. The uncertain distributions make up the uncertainty space $\Gamma \subset \mathbb{R}^N$, where N is the number of uncertain parameters. We consider the input parameter uncertainties to be independently distributed.

Mat.	g	D_g	$\Sigma_{a,g}$	$\nu \Sigma_{f,g}$	$\Sigma_s^{1,2}$
1	1	1.255	8.252e-3	4.602e-3	2.533e-2
	2	2.11e-1	1.003e-1	1.091e-1	
2	1	1.268	7.181e-3	4.609e-3	2.767e-2
	2	1.902e-1	7.047e-2	8.675e-2	
3	1	1.259	8.002e-3	4.663e-3	2.617e-2
	2	2.091e-1	8.344e-2	1.021e-1	
4	1	1.259	8.002e-3	4.663e-3	2.617e-2
	2	2.091e-1	7.3324e-2	1.021e-1	
5	1	1.257	6.034e-4	0	4.754e-2
	2	1.592e-1	1.911e-2	0	

TABLE I: Reference Material Properties for Benchmark Core

METHODS

We solve our system of equations by imposing a mesh grid on the physical domain using the local and global particle-conserving finite volume method. We solve the system of equations nonlinearly with the criticality eigenvalue, using Jacobian-free Newton-Krylov methods. We use the GMRES algorithm in the trilinos solver package.

Developing an adaptive algorithm for uncertainty quantification builds on the sparse grid formulation used previously [5] and analysis of variance [3]. We represent the k -eigenvalue as a function of input parameters as $u(Y)$. The generalized polynomial chaos expansion is given by

$$u(Y) \approx u_h(Y) = \sum_{k=0}^{\eta} c_k \Phi_k(Y), \quad (4)$$

$$\Phi_k(Y) = \prod_{n=1}^N \phi_{k_n}(Y_n), \quad (5)$$

where $u_h(Y)$ is the spatially-discretized PDE solution, and $\phi_{k_n}(Y_n)$ are Askey polynomials of order k_n that are orthonormal with respect to the probability distribution function $\rho_n(Y_n)$ over the probability space Ω . Using orthonormality, we obtain an expression for the expansion coefficients c_k as

$$c_k = \langle u(Y) \Phi(Y) \rangle = \int_{\Omega} u(Y) \Phi(Y) \rho(Y) dY. \quad (6)$$

Because Y are uniformly distributed, we use Gauss-Legendre quadrature to obtain collocation points and weights to evaluate c_k .

Previously we identified static methods to determine the index set Λ [5]. We propose an adaptive method based

on analysis of variance to construct the index set, following a pattern similar to the algorithm in [3]. A property of the gPC expansion is the method of calculating variance, namely

$$\sigma^2 = \mathbb{E}[u_h(Y)^2] - \mathbb{E}[u_h(Y)]^2 = \sum_{k \in \Lambda} c_k^2 - c_0^2. \quad (7)$$

The partial percent variance η due to each polynomial is

$$\eta_k \equiv \frac{c_k^2}{\sigma^2}. \quad (8)$$

The adaptive method is initialized by evaluating the gPC to a first-order polynomial expansion in each dimension. The algorithm then continues by searching the polynomial indices that may be added to the index set, which is dependent on the existing polynomials. The admissibility condition is

$$k - e_j \in \Lambda \text{ for } 1 \leq j \leq N, k_j > 1, \quad (9)$$

where e_j is a unit vector in the direction j . The estimated partial variance for a prospective polynomial is the product of immediate subset polynomials,

$$\tilde{\eta}_k = \prod_{j=1, k_j > 0}^N \eta_{k_j - e_j}. \quad (10)$$

The adaptive algorithm chooses the prospective polynomial with the largest estimated partial variance to add to the index set, and the algorithm continues until estimated remaining variance is less than tolerance.

RESULTS

Material	Property	Distribution
Material 1	$\nu \Sigma_{f,2}$	$\mathcal{U}(0.1036, 0.1146)$
Material 1	$\Sigma_{c,2}$	$\mathcal{U}(0.0526, 0.0582)$
Material 4	$\nu \Sigma_{f,2}$	$\mathcal{U}(0.0970, 0.1072)$
Material 4	$\Sigma_{c,2}$	$\mathcal{U}(0.03935, 0.04349)$
Material 5	D_2	$\mathcal{U}(0.1512, 0.1672)$

TABLE II: Uncertain Input Parameters

The uncertainty quantification algorithm is implemented in **raven** [6], and analysis here is performed using this framework. The uncertain inputs are listed in Table II. We note that while Σ_a was used in the benchmark, we explicitly use Σ_c as an input and derive Σ_a . We obtain the error in the moments r of the quantity of interest $k(Y) = u(Y)$, given by

$$\epsilon_h^{(r)} = \frac{|\mathbb{E}[u_h^{(r)}] - \mathbb{E}[u_{\text{ref}}^{(r)}]|}{\mathbb{E}[u_{\text{ref}}^{(r)}]}, \quad (11)$$

$$\mathbb{E}[u_h^{(r)}] = \mathbb{E}[S_{N, \Lambda_{\text{TD}}(L)}[u_h](Y)^{(r)}] = \sum_{k=1}^{\eta} w_k u_h^{(r)}(Y^{(k)}). \quad (12)$$

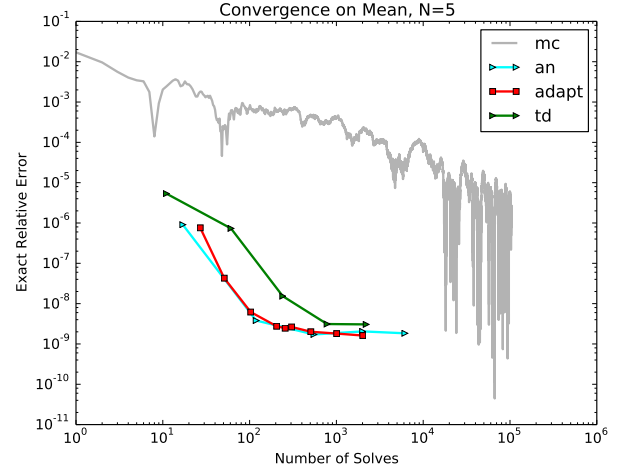


Fig. 2: Mean Convergence

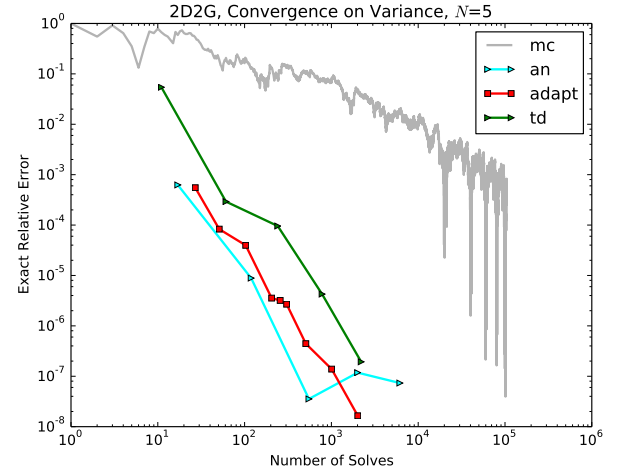


Fig. 3: Variance Convergence

Figs. 2-3 show the comparison of Monte Carlo convergence to stochastic collocation for five uncertain input parameters. The Monte Carlo (mc), total degree (td), and anisotropic total degree (an) methods have been demonstrated previously [5]. The adaptive line is obtained as a result of the work described in this paper. Because of the swift convergence on the mean and the uncertainty of the benchmark value, all presented methods appear to cease converging after 8 orders of magnitude in relative error. However, the same trend can generally be seen in both the mean and variance convergence.

DISCUSSION

As expected, the convergence of Monte Carlo on the benchmark as a function of computational solves is nearly linear and lethargic compared to the other methods. The static isotropic index set, in which each input dimension is treated with equal importance, converges much more efficiently than Monte Carlo, but lacks the benefit of empha-

sizing some dimensions over others. The anisotropic case is most efficient, where first-order sensitivity information was used to determine anisotropic weights for polynomials to use in the polynomial chaos expansion. Interestingly, the adaptive algorithm converges slightly less efficiently than the anisotropic case, while still performing better than the isotropic case. Because the adaptive case has to determine the importance of each input dimension, it occasionally predicts inaccurately and wastes computation solves compared to the more ideal anisotropic case. However, in circumstances when an ideal anisotropy is not understood a priori, the adaptive algorithm may be nearly as efficient at representing the original model. Given the potential loss of efficiency when using a poorly-chosen anisotropic weighting, the adaptive algorithm may be an effective choice for initial uncertainty quantification in problems with a low-dimensionality input space.

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