

Higher-Order Moments of Spline Chaos Expansion

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Outline

① INTRODUCTION

② SCE

③ EXAMPLES

④ CLOSURE

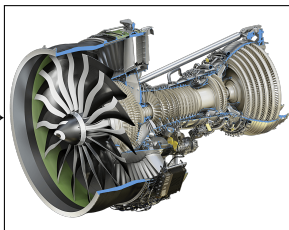
Uncertainty Quantification

Complex System (jet engine)

Input $\mathbf{X} = (X_1, \dots, X_N)$

$$\mathbf{X} : (\Omega, \mathcal{F}) \rightarrow (\mathbb{A}^N, \mathcal{B}^N) \rightarrow$$

$$\mathbb{A}^N \subseteq \mathbb{R}^N, \quad N \in \mathbb{N}$$



Output $Y = y(\mathbf{X})$

$$Y \in L^p(\Omega, \mathcal{F}, \mathbb{P})$$

$$y \in L^p(\mathbb{A}^N, \mathcal{B}^N, f_{\mathbf{X}} d\mathbf{x})$$

• Goals & Objectives

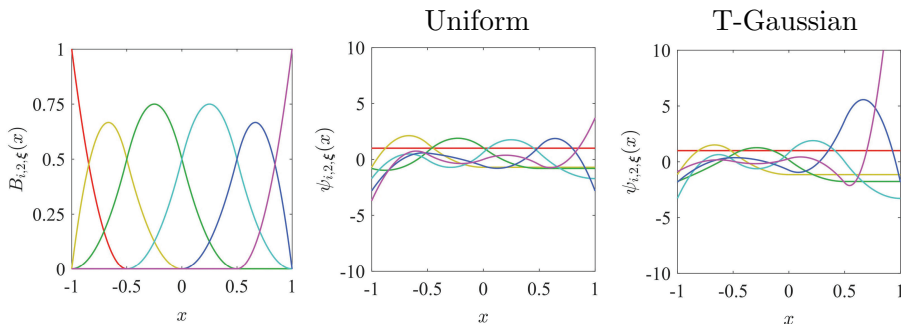
- Moments: $\mathbb{E}[Y^l] := \int_{\Omega} Y^l d\mathbb{P} = \int_{\mathbb{A}^N} y^l(\mathbf{x}) f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x},$
- Probability distribution: $\mathbb{P}[Y \leq y_0] := \int_{\{\mathbf{x}: y(\mathbf{x}) \leq y_0\}} f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}$
- Stochastic design optimization (RDO/RBDO)

Orthonormalized (ON) Univariate B-Splines

For $k = 1, \dots, N$, let $B_{i_k, m_k, \xi_k}^k(x_k)$ & $\psi_{i_k, m_k, \xi_k}^k(x_k)$ be real-valued B-splines and ON B-splines in x_k of degree $m_k \in \mathbb{N}_0$ and knot sequence

$$\xi_k = \{a_k = \xi_{k,1}, \dots, \xi_{k,n_k+m_k+1} = b_k\}, \quad n_k = \text{len}(\xi_k) - m_k - 1.$$

Example: $m_k = 2$, $\xi_k = \{-1, -1, -1, -0.5, 0, 0.5, 1, 1, 1\}$, $n_k = 6$.



Multivariate ON B-Splines (Full Tensor-Product)

For $\mathbf{i} := (i_1, \dots, i_N)$, $\mathbf{m} := (m_1, \dots, m_N)$, $\Xi := (\xi_1, \dots, \xi_N)$, the tensor-product ON B-splines in $\mathbf{x} = (x_1, \dots, x_N)$ are

$$\Psi_{\mathbf{i}, \mathbf{m}, \Xi}(\mathbf{x}) = \prod_{k=1}^N \psi_{i_k, m_k, \xi_k}^k(x_k), \quad \mathcal{S}_{\mathbf{m}, \Xi} = \text{span} \{ \Psi_{\mathbf{i}, \mathbf{m}, \Xi}(\mathbf{x}) \}_{\mathbf{i} \in \mathcal{I}_{\mathbf{n}}}.$$

$$\mathcal{I}_{\mathbf{n}} := \{ \mathbf{i} = (i_1, \dots, i_N) : 1 \leq i_k \leq n_k, k = 1, \dots, N \}$$

The second-moment properties are

$$\mathbb{E} [\Psi_{\mathbf{i}, \mathbf{m}, \Xi}(\mathbf{X})] = \begin{cases} 1, & \mathbf{i} = \mathbf{1} := (1, \dots, 1), \\ 0, & \mathbf{i} \neq \mathbf{1}. \end{cases}$$

$$\mathbb{E} [\Psi_{\mathbf{i}, \mathbf{m}, \Xi}(\mathbf{X}_u) \Psi_{\mathbf{j}, \mathbf{m}, \Xi}(\mathbf{X}_v)] = \begin{cases} 1, & \mathbf{i} = \mathbf{j}, \\ 0, & \mathbf{i} \neq \mathbf{j}. \end{cases}$$

Spline Chaos Expansion (SCE) [Rahman, 2020]

Theorem

For independent random input $\mathbf{X}$, an output random variable $y(\mathbf{X}) \in L^p(\Omega, \mathcal{F}, \mathbb{P})$, $2 \leq p < \infty$, admits an orthogonal expansion in $\{\Psi_{\mathbf{i}, \mathbf{m}, \Xi}(\mathbf{X})\}_{\mathbf{i} \in \mathcal{I}_n}$, referred to as the SCE of

$$y_{\mathbf{m}, \Xi}(\mathbf{X}) := \sum_{\mathbf{i} \in \mathcal{I}_n} C_{\mathbf{i}, \mathbf{m}, \Xi} \Psi_{\mathbf{i}, \mathbf{m}, \Xi}(\mathbf{X}),$$

where

$$C_{\mathbf{i}, \mathbf{m}, \Xi} := \int_{\mathbb{A}^N} y(\mathbf{x}) \Psi_{\mathbf{i}, \mathbf{m}, \Xi}(\mathbf{x}) f_{\mathbf{X}}(\mathbf{x}) d\mathbf{x}.$$

$$L_{\mathbf{m}, \Xi} = |\mathcal{I}_n| = \prod_{k=1}^N n_k$$

SCE suffers from the curse of dimensionality

Error Bound & L^p Convergence ($2 \leq p < \infty$)

- α_k th modulus of smoothness of y in L^p ($\alpha_k \geq 1$)

$$\omega_{\alpha_k}(y; h_k)_{L^p[a_k, b_k]} := \sup_{0 \leq u_k \leq h_k} \|\Delta_{u_k}^{\alpha_k} y(x_k)\|_{L^p[a_k, b_k - \alpha_k u_k]}, \quad h_k \geq 0,$$

$$\Delta_{u_k}^{\alpha_k} y(x_k) := \sum_{i=0}^{\alpha_k} (-1)^{\alpha_k-i} \binom{\alpha_k}{i} y(x_k + i u_k) \rightarrow \alpha_k \text{th fwd. diff.}$$

$$\omega_{\alpha}(y; \mathbf{h})_{L^p[\mathbb{A}^N]} := \sup_{\mathbf{0} \leq \mathbf{u} \leq \mathbf{h}} \|\Delta_{\mathbf{u}}^{\alpha} y(\mathbf{x})\|_{L^p[\mathbb{A}_{\alpha, \mathbf{u}}^N]}, \quad \mathbf{h} \geq \mathbf{0}$$

- L^p -error

$$\mathbb{E}[|y(\mathbf{X}) - y_{\mathbf{m}, \Xi}(\mathbf{X})|^p] \leq C \omega_{\mathbf{m}+1}(y; \mathbf{h})_{L^p(\mathbb{A}^N)}$$

$$\lim_{\mathbf{h} \rightarrow \mathbf{0}} \mathbb{E}[|y(\mathbf{X}) - y_{\mathbf{m}, \Xi}(\mathbf{X})|^p] = 0$$

SCE converges in the p th mean, in prob., & in distribution

Output Statistics

- Mean and Variance

$$\mu_{\mathbf{m},\Xi} := \mathbb{E}[y_{\mathbf{m},\Xi}(\mathbf{X})] = C_{1,\mathbf{m},\Xi} = \mathbb{E}[y(\mathbf{X})]$$

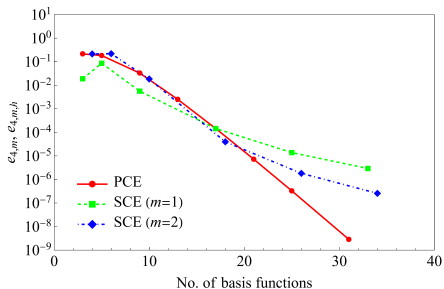
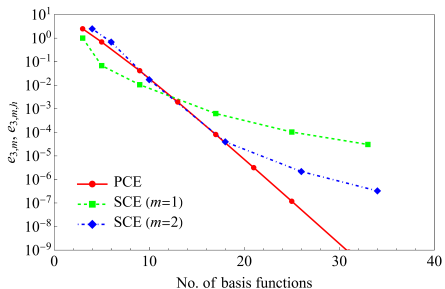
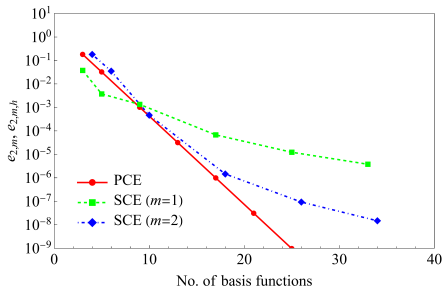
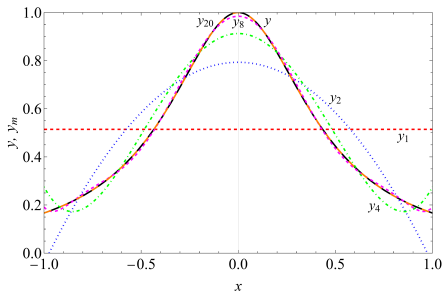
$$\sigma_{\mathbf{m},\Xi}^2 := \text{var}[y_{\mathbf{m},\Xi}(\mathbf{X})] = \sum_{\mathbf{i} \in \mathcal{I}_{\mathbf{n}}} C_{\mathbf{i},\mathbf{m},\Xi}^2 - C_{1,\mathbf{m},\Xi}^2 \leq \text{var}[y(\mathbf{X})]$$

- Skewness and Kurtosis

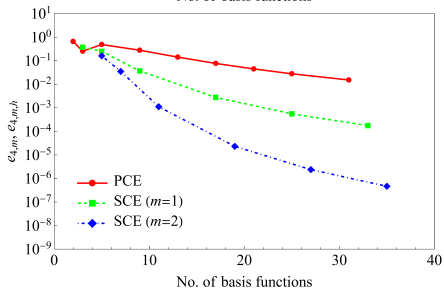
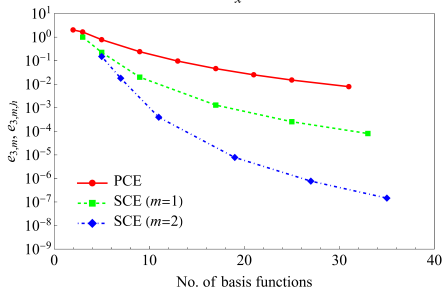
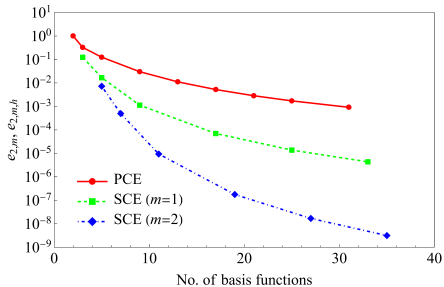
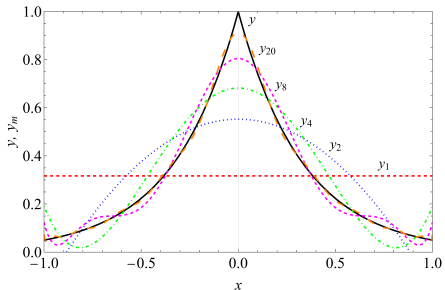
$$\gamma_{\mathbf{m},\Xi} := \mathbb{E} \left[\frac{y_{\mathbf{m},\Xi}(\mathbf{X}) - \mu_{\mathbf{m},\Xi}}{\sigma_{\mathbf{m},\Xi}} \right]^3$$

$$\kappa_{\mathbf{m},\Xi} := \mathbb{E} \left[\frac{y_{\mathbf{m},\Xi}(\mathbf{X}) - \mu_{\mathbf{m},\Xi}}{\sigma_{\mathbf{m},\Xi}} \right]^4$$

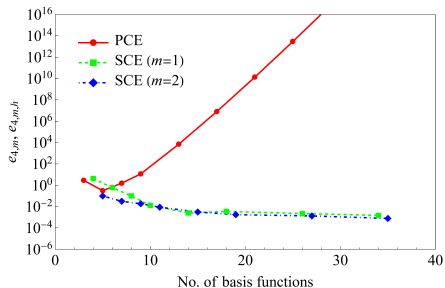
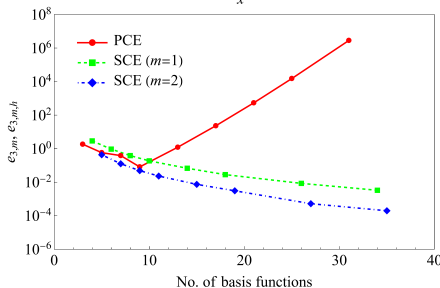
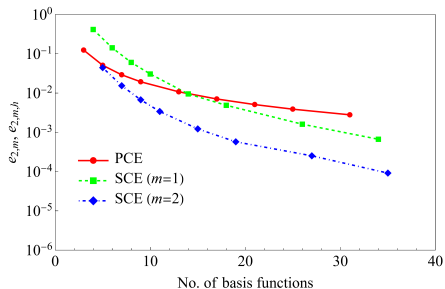
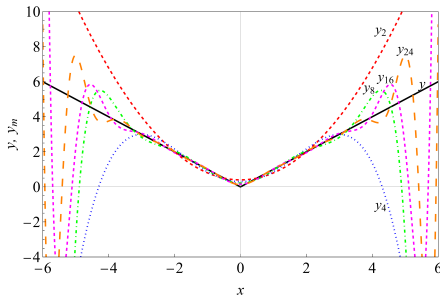
1. $y(X) = 1/(1 + 5X^2)$, $X \sim U[-1, +1]$



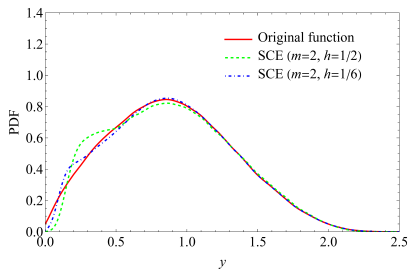
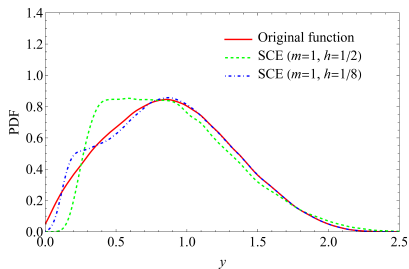
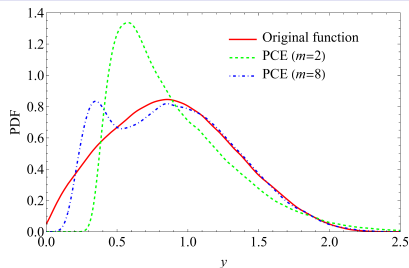
2. $y(X) = \exp(-3|X|)$, $X \sim U[-1, +1]$



3. $y(X) = |X|$, $X \sim N[0, 1]$



$$4. \quad y(\mathbf{X}) = \prod_{i=1}^4 \frac{|4X_i - 2|^{b_i} + a_i}{1 + a_i}, \quad X_1, \dots, X_4 \stackrel{i.i.d.}{\sim} U[0, 1]$$



Conclusion

- Proof that SCE converges in L^p
- SCE more efficient than PCE for non-smooth functions
- Higher-order moments of PCE may diverge
- SCE and PCE suffer from the curse of dimensionality

Reference

Rahman, S., “Higher-Order Moments of Spline Chaos Expansion,” *Probabilistic Engineering Mechanics*, Vol. 77, Article 103666, pp. 1-15, 2024.