

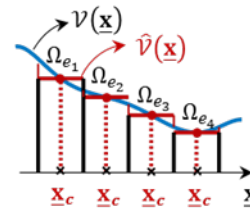
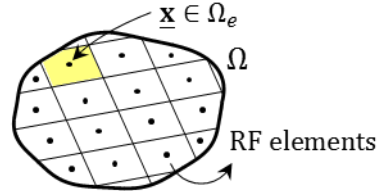
**457.646 Topics in Structural Reliability**  
**In-Class Material: Class 26**

© **Discrete Representation of RFs (Summary: Sudret & ADK 2000; 2002 PEM)**

① Mid-point method

$$v(\mathbf{x}) \approx \hat{v}(\mathbf{x}) \\ = v(\mathbf{x}_c), \mathbf{x} \in \Omega_e$$

(constant in each  $\Omega_e$ )



- Represented by a constant r.v. over each RF element
- Positive definiteness problem of  $\mathbf{R} \dots$  if RF element size is small relative to  $\theta$

Recommended size of RF element size

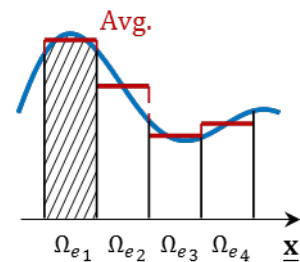
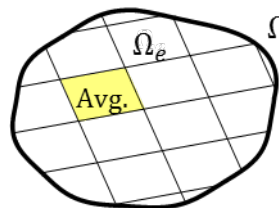
$$\frac{\theta}{10} \sim \frac{\theta}{15} \leq \text{RF size} \leq \frac{\theta}{3} \sim \frac{\theta}{5}$$

Numerical stability  
 (Positive definiteness)

Accurate representation

② Spatial averaging method

$$\hat{v}(\mathbf{x}) = \frac{\int_{\Omega_e} v(\mathbf{x}) d\Omega}{\int_{\Omega_e} d\Omega}, \mathbf{x} \in \Omega_e$$

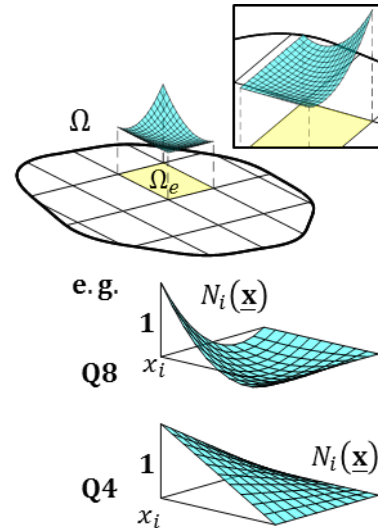
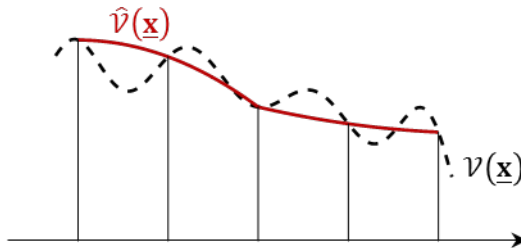


- Represented by a single r.v per  $\Omega_e$
- Variances are ( )  $\rightarrow$  \_\_\_\_\_-estimate  $P_f$
- Positive definiteness problem

③ Shape function method (← motivated by FE people)

$$v(\mathbf{x}) \approx \hat{v}(\mathbf{x}) = \sum_{\substack{\text{element} \\ \text{nodes}}} N_i(\mathbf{x})v(\mathbf{x}_i)$$

- Represented by continuous function



$$N_i(\mathbf{x}_j) = \delta_{ij}$$

to guarantee  $\hat{v}(\mathbf{x}_i) = v(\mathbf{x}_i)$

④ Karhunen-Loève (KL) expansion (Gaussian RFs)

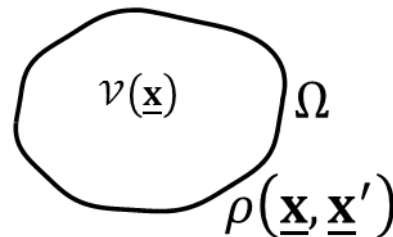
→ Describe RF in terms of finite # of shape functions

defined over \_\_\_\_\_ domain

(no geometric discretization)

→ Discretization based on

\_\_\_\_\_ structure  $\rho(\mathbf{x}, \mathbf{x}')$



Goal: Want to describe  $\rho(\mathbf{x}, \mathbf{x}')$  by

$$\rho(\mathbf{x}, \mathbf{x}') = \sum_{i=1}^{\infty} \lambda_i \varphi_i(\mathbf{x}) \varphi_i(\mathbf{x}')$$

Orthogonal shape (base) functions

Can find  $\lambda, \varphi$  by solving an integral eigenvalue problem, i.e.

$$\int_{\Omega} \rho(\mathbf{x}, \mathbf{x}') \varphi_i(\mathbf{x}') d\mathbf{x}' = \lambda_i \varphi_i(\mathbf{x}) \quad (\text{Fredholm integral eqn} - 2^{\text{nd}} \text{ kind})$$

Note  $\rho(\mathbf{x}, \mathbf{x}')$  is bounded, symmetric, (+) definite.

If so, one can find

$$\varphi_i(\mathbf{x}) : \text{orthogonal} \quad \int \varphi_i(\mathbf{x}) \varphi_j(\mathbf{x}) d\mathbf{x} = \delta_{ij}$$

$\lambda_i$ : real & positive

Can drop  $\lambda_i$ 's if  $\lambda_r \cong 0$

Then using  $\varphi_i(\mathbf{x})$ , and  $\lambda_i, i=1, \dots, r$ , one can describe Gaussian RF  $v(x)$  by

KL expansion of Gaussian RF

$$v(\mathbf{x}) \approx \hat{v}(\mathbf{x}) = \mu(\mathbf{x}) + \sigma(\mathbf{x}) \sum_{i=1}^r (u_i \sqrt{\lambda_i} \varphi_i(\mathbf{x})), \quad x \in \Omega \Rightarrow v(\mathbf{x}) \Rightarrow \{u_1, \dots, u_r\}$$

$u_i \rightarrow N(0,1)$ ,  $u_i$  s.i

Let's check!

i. Gaussian? Yes, function of  $u_i$ 's

ii.  $E[\hat{v}(\mathbf{x})] = \mu(\mathbf{x})$ ?  $E[\hat{v}(\mathbf{x})] =$

iii.  $Var[\hat{v}(\mathbf{x})] = E[(\quad)^2]$

$$= E\left[ \sum_{i=1}^r \sum_{j=1}^r \quad \right]$$

$$= \sigma^2(\mathbf{x}) \sum_{i=1}^r \sum_{j=1}^r \sqrt{\lambda_i} \sqrt{\lambda_j} \varphi_i(\mathbf{x}) \varphi_j(\mathbf{x})$$

$$= \sigma^2(\mathbf{x}) \sum_{i=1}^r \lambda_i \varphi_i^2(\mathbf{x})$$

$$= \sigma^2(\mathbf{x})$$

(because  $\rho(\mathbf{x}, \mathbf{x}) = \quad = \quad$ )

iv.  $\rho_{\hat{v}}(\mathbf{x}, \mathbf{x}') = \rho(\mathbf{x}, \mathbf{x}')$

$$= E[(\hat{v}(\mathbf{x}) - \mu(\mathbf{x}))(\hat{v}(\mathbf{x}') - \mu(\mathbf{x}'))] / \sigma(\mathbf{x})\sigma(\mathbf{x}')$$

$$= E\left[ \sum_{i=1}^r \sum_{j=1}^r u_i \sqrt{\lambda_i} \varphi_i(\mathbf{x}) u_j \sqrt{\lambda_j} \varphi_j(\mathbf{x}') \right]$$

$$= \sum_{i=1}^r \sum_{j=1}^r E[ \quad ] \sqrt{\lambda_i} \sqrt{\lambda_j} \varphi_i(\mathbf{x}) \varphi_j(\mathbf{x}')$$

$$= \sum_{i=1}^r \lambda_i \varphi_i(\mathbf{x}) \varphi_i(\mathbf{x}')$$

$$= \varphi(\mathbf{x}, \mathbf{x}')$$

- # of RV's:
- Represented by \_\_\_\_\_ function
- No \_\_\_\_\_ necessary
- Most efficient (in terms of # of \_\_\_\_\_ )
- Requires solution of an integral eigenvalue problem.

⑤ Orthogonal expansion (eigen-expansion, but correlated rv's)

⑥ Optimal linear estimation (OLE)~ linear regression

⑦ Expansion OLE

∴ See Sudret & ADK (2000)

### ◎ Nataf RF

$$v(\mathbf{x}) \Rightarrow F(v, \mathbf{x}), \rho_{zz}(\mathbf{x}, \mathbf{x}')$$

$$v(\mathbf{x}) = F_v^{-1}\{\Phi(\hat{Z}(\mathbf{x}))\}, Z(\mathbf{x}) \sim N(\mathbf{0}, \rho_{zz}(\mathbf{x}, \mathbf{x}')) \quad (Z(\mathbf{x}) \rightarrow \text{Gaussian RF})$$

⇒ Construct  $Z(\mathbf{x})$  and discrete to  $\hat{Z}(\mathbf{x})$

$$\Rightarrow v(\mathbf{x}) = F^{-1}\{\Phi(\hat{Z}(\mathbf{x}))\}$$

### VIII-4. Response Surface Method (CRC Ch.19 & Mike Tipping's chapter)

#### ◎ Reliability Analysis, Uncertainty Quantification & Response Surface

##### Reliability Analysis

$$P_f = \int_{g(\mathbf{x}) \leq 0} f_{\mathbf{x}}(\mathbf{x}) d\mathbf{x} \rightarrow \text{e.g. FORM/SORM } g(\mathbf{x}_i), \nabla g(\mathbf{x}_i)$$

$$\rightarrow \text{e.g. Sampling } q_i = I(\mathbf{x}_i) \text{ or } \frac{I(\mathbf{x}_i) \cdot f(\mathbf{x}_i)}{h(\mathbf{x}_i)}$$

$$\text{where } I(\mathbf{x}_i) = \begin{cases} 1 & g(\mathbf{x}_i) \leq 0 \\ 0 & g(\mathbf{x}_i) > 0 \end{cases}$$

##### Uncertainty Quantification

"Process of determining the effect of input uncertainties"

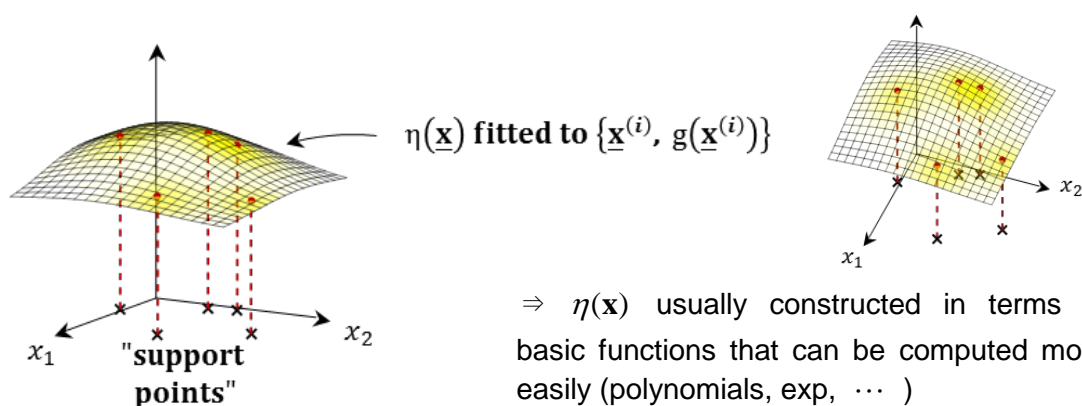
on response metrics of interest (Eldred et al. 2008)

$$\text{e.g. } E[g(\mathbf{x})^m] = \int_{\mathbf{x}} g(\mathbf{x})^m f_{\mathbf{x}}(\mathbf{x}) d\mathbf{x}$$

①  $g(\mathbf{x})$  Sometimes

- Computationally costly for MCS
- No analytical gradients but many RVs
- ⇒ FORM/SORM difficult
- Experiments expensive (statistical analysis of experiment data infeasible)

② Idea:  $g(\mathbf{x}) \approx \eta(\mathbf{x})$  ( $\eta(\mathbf{x}) \leftarrow$  "response surface" or "surrogate" model)



⇒  $\eta(\mathbf{x})$  usually constructed in terms of basic functions that can be computed more easily (polynomials, exp, ...)

⇒ Should fit  $g(\mathbf{x}^{(i)})$  sufficiently well especially in the region that contributes most to  $P_f$  or  $E[g(\mathbf{x})^m]$

③ History

- Box and Wilson (1954): influential
- Applied mostly in chemical, industrial eng. etc.  
(Mostly for “experimental design”)
- Rackwitz (1982) ⇒ Use RS for Structural Reliability Analysis
- Has been applied to random field, nonlinear structural dynamics, etc.