

## 457.646 Topics in Structural Reliability

### In-Class Material: Class 12

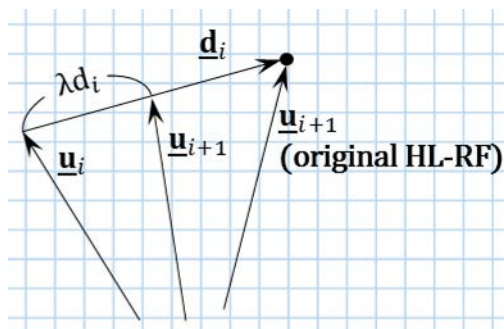
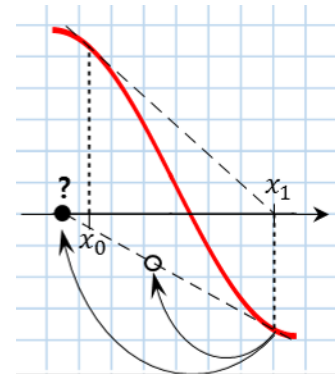
See Supplement, “HL-RF Algorithm for HL Reliability Index and FORM/SORM”

#### ☆ Convergence Issue

Solution: Does not go full step, i.e. “step size” control

- Modified HL-RF (Liu & ADK 1990)
- Improved HL-RF (Zhang & ADK 1995)

$$\begin{cases} u_{i+1} = u_i + \lambda d_i \quad (\lambda, \text{stepsize} < 1) \\ d_i = \left( \hat{\alpha}_i u_i + \frac{G(u_i)}{\|\nabla G(u_i)\|} \right) \hat{\alpha}_i^T - u_i \end{cases}$$



How? “Merit” function  $m(\mathbf{u})$  is defined such that  $m(\mathbf{u})$  is minimum at  $\mathbf{u} =$

Then, select  $\lambda$  at each step such that  $m(\mathbf{u})$  d\_\_\_\_\_

e.g. 1) Modified HL-RF:  $m(\mathbf{u}) = \frac{1}{2} \left\| \mathbf{u} - \hat{\alpha} \mathbf{u} \hat{\alpha}^T \right\|^2 + \frac{1}{2} c \cdot G(\mathbf{u})^2$

( $m(\mathbf{u})$  can have minima that are not solution)

2) Improved HL-RF:  $m(\mathbf{u}) = \frac{1}{2} \|\mathbf{u}\|^2 + c |G(\mathbf{u})|$

Select  $\lambda$  such that  $m(\mathbf{u}_{i+1}) < m(\mathbf{u}_i)$  because the direction vector is a descent direction in terms of merit function

as long as  $c > \frac{\|\mathbf{u}_{i+1}\|}{\|\nabla G(\mathbf{u}_{i+1})\|}$

※ Zhang & ADK(1995) proved this based on so-called “Armijo’s rule” and provided detailed updating rule for  $c$  (but FERUM uses a simple rule)

**Example:  $\beta_{HL}$  by improved HL-RF algorithm**

**Limit-state function**  $g(X_1, X_2) = 0.5X_1^2 - X_2 + 3\sin(2X_1)$

**Mean vector and covariance matrix of  $X_1$  and  $X_2$ :**

$$\mathbf{M} = \begin{bmatrix} 5 \\ 3 \end{bmatrix}, \quad \mathbf{\Sigma} = \begin{bmatrix} 4 & 5 \\ 5 & 25 \end{bmatrix}$$

**Gradient**  $\nabla g = [X_1 + 6\cos(2X_1) \quad -1]$

**Preparation:**

$$\mathbf{D} = \begin{bmatrix} 2 & 0 \\ 0 & 5 \end{bmatrix}, \quad \mathbf{R} = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$$

$$\mathbf{R} = \mathbf{L}\mathbf{L}^T \text{ (Cholesky decomposition): } \mathbf{L} = \begin{bmatrix} 1 & 0 \\ 0.5 & 0.87 \end{bmatrix}, \quad \mathbf{L}^{-1} = \begin{bmatrix} 1 & 0 \\ -0.58 & 1.15 \end{bmatrix}$$

$$\mathbf{u}(\mathbf{x}) = \mathbf{L}^{-1}\mathbf{D}^{-1}(\mathbf{x} - \mathbf{M}_x); \quad \mathbf{x}(\mathbf{u}) = \mathbf{D}\mathbf{L}\mathbf{u} + \mathbf{M}$$

$$\mathbf{J}_{\mathbf{u},\mathbf{x}} = \mathbf{L}^{-1}\mathbf{D}^{-1} = \begin{bmatrix} 0.5 & 0 \\ -0.29 & 0.23 \end{bmatrix}; \quad \mathbf{J}_{\mathbf{x},\mathbf{u}} = \mathbf{D}\mathbf{L} = \begin{bmatrix} 2 & 0 \\ 2.5 & 4.33 \end{bmatrix} \text{ (constant since linear)}$$

**Initialization:**

$$i = 1; \quad \varepsilon_1 = \varepsilon_2 = 10^{-3}$$

$$\text{Starting point: } \mathbf{x}_1 = \mathbf{M} = \begin{bmatrix} 5 \\ 3 \end{bmatrix}; \quad \mathbf{u}_1 = \mathbf{u}(\mathbf{x}_1) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$\text{Scale parameter: } G_0 = g(\mathbf{M}) = 0.5 \cdot 5^2 - 3 + 3 \cdot \sin(2 \cdot 5) = 7.87$$

**Computation (1<sup>st</sup> step):**

$$G(\mathbf{u}_1) = g(\mathbf{x}_1) = 7.8679$$

$$\nabla G(\mathbf{u}_1) = \nabla g(\mathbf{x}_1)\mathbf{J}_{\mathbf{x},\mathbf{u}} = \begin{bmatrix} -0.03 & -1 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 2.5 & 4.33 \end{bmatrix} = \begin{bmatrix} -2.57 & -4.33 \end{bmatrix}$$

$$\hat{\alpha}_1 = -\frac{\begin{bmatrix} -2.57 & -4.33 \end{bmatrix}}{\left(2.57^2 + 4.33^2\right)^{1/2}} = \begin{bmatrix} 0.51 & 0.86 \end{bmatrix}$$

**Convergence check (1<sup>st</sup> step): Skipped.**

**Update (1<sup>st</sup>→2<sup>nd</sup>):**

$$c_1 \geq \frac{\|\mathbf{u}_1\|}{\|\nabla G(\mathbf{u}_1)\|} = 0; \text{ Set } c_1 = 10$$

Current value of the merit function:

$$m(\mathbf{u}_1) = 0.5\|\mathbf{u}_1\|^2 + c_1 |G(\mathbf{u}_1)| = 0.5(0)^2 + 10(7.87) = 78.7$$

$$\begin{aligned} \mathbf{d}_1 &= \left[ \hat{\alpha}_1 \mathbf{u}_1 + \frac{G(\mathbf{u}_1)}{\|\nabla G(\mathbf{u}_1)\|} \right] \hat{\alpha}_1^T - \mathbf{u}_1 \\ &= \left\{ \begin{bmatrix} 0.51 & 0.86 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix} + \frac{7.87}{5.03} \right\} \begin{bmatrix} 0.51 \\ 0.86 \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\ &= \begin{bmatrix} 0.80 \\ 1.34 \end{bmatrix} \end{aligned}$$

Try a step size:  $\lambda = 1$  (original HL-RF)

$$\begin{aligned} \mathbf{u}_2 &= \mathbf{u}_1 + \lambda \mathbf{d}_1 \\ &= \begin{bmatrix} 0 \\ 0 \end{bmatrix} + (1) \begin{bmatrix} 0.80 \\ 1.34 \end{bmatrix} = \begin{bmatrix} 0.80 \\ 1.34 \end{bmatrix} \end{aligned}$$

Check  $m(\mathbf{u}_2) < m(\mathbf{u}_1)$

$$\mathbf{x}_2 = \mathbf{x}(\mathbf{u}_2) = \begin{bmatrix} 6.59 \\ 10.81 \end{bmatrix}$$

$$G(\mathbf{u}_2) = g(\mathbf{x}_2) = 0.5 \cdot 6.59^2 - 10.81 + 3 \sin(2 \cdot 6.59) = 12.68$$

$$m(\mathbf{u}_2) = 0.5(6.59^2 + 10.81^2) + 10(12.68) = 126.82 > 78.7 \quad \text{N.G. (reject: } \lambda = 1)$$

Try a step size:  $\lambda = 0.5$

$$\begin{aligned} \mathbf{u}_2 &= \mathbf{u}_1 + \lambda \mathbf{d}_1 \\ &= \begin{bmatrix} 0 \\ 0 \end{bmatrix} + (0.5) \begin{bmatrix} 0.80 \\ 1.34 \end{bmatrix} = \begin{bmatrix} 0.40 \\ 0.67 \end{bmatrix} \end{aligned}$$

Check  $m(\mathbf{u}_2) < m(\mathbf{u}_1)$

$$\mathbf{x}_2 = \mathbf{x}(\mathbf{u}_2) = \begin{bmatrix} 5.80 \\ 6.91 \end{bmatrix}$$

$$G(\mathbf{u}_2) = g(\mathbf{x}_2) = 0.5 \cdot 5.08^2 - 6.91 + 3 \sin(2 \cdot 5.08) = 7.42$$

$$m(\mathbf{u}_2) = 0.5(0.40^2 + 0.67^2) + 10(7.42) = 74.60 < 78.7 \quad \text{O.K. (accept: } \lambda = 0.5)$$

**Computation (2<sup>nd</sup> step):**

$$\nabla g = [X_1 + 6 \cos(2X_1) \quad -1]$$

$$G(\mathbf{u}_2) = 7.42$$

$$\nabla G(\mathbf{u}_2) = \begin{bmatrix} 9.18 & -1 \end{bmatrix} \begin{bmatrix} 2 & 0 \\ 2.5 & 4.33 \end{bmatrix} = \begin{bmatrix} 15.86 & -4.33 \end{bmatrix}$$

$$\hat{\alpha}_2 = \begin{bmatrix} -0.97 & 0.26 \end{bmatrix}$$

**Convergence check (2<sup>nd</sup> step):**

$$|G(\mathbf{u}_2) / G_0| = \frac{7.42}{7.67} = 0.94 > \varepsilon_1 \quad \mathbf{N.G.}$$

$$\|\mathbf{u}_2 - \hat{\alpha}_2 \mathbf{u}_2 \hat{\alpha}_2^T\| = 0.75 > \varepsilon_2 \quad \mathbf{N.G.}$$

**Update (2<sup>nd</sup> → 3<sup>rd</sup>):**

$$c_2 \geq \|\mathbf{u}_2\| / \|\nabla G(\mathbf{u}_2)\| = 0.05 ; \text{ set } c_2 = 10$$
$$\vdots$$

**Repeat until the convergence criteria are satisfied.**

**Note:** If  $m(\mathbf{u}_{i+1}) \geq m(\mathbf{u}_i)$ , reduce the value of  $\lambda$  until you satisfy  $m(\mathbf{u}_{i+1}) < m(\mathbf{u}_i)$

☆ **Santos, Matioli & Beck (2012)**

New optimization algorithms for structural reliability Analysis

- ⇒ provides a good review on HLRF, mHLRF and iHLRF
- ⇒ proposes nHLRF and two Lagrangian methods
- ⇒ nHLRF → as efficient as iHLRF & more robust
- ⇒ Lagrangian → Less efficient than HLRF's but more general and probably more suitable than HLRFs for large no. of rvs

◎ **Reliability Indices**

**VS Reliability Methods**

$$(\beta_{SM}, \beta_{SF}, \beta_{MVFOSM}, \beta_{HL}) \quad (P_f)$$

Reliability indices

- Use partial & ( i.e.  $\nabla$  )
- Do not provide a framework to consider type of of input r.v's
- $P_f$  could be estimated for special cases only

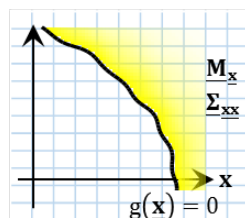
(e.g.,  $P_f = \Phi(-\beta_{SM})$  when  $R, S \sim \text{Normal}$ )

→ Therefore, cannot be considered as reliability \_\_\_\_\_

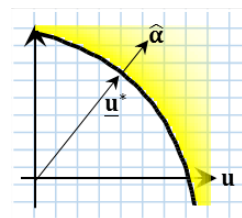
cf. FORM/SORM ~ reliability methods

$$\begin{aligned} & \text{design point} \\ & = \text{concept} \\ & \text{(e.g. } \beta_{HL} \text{)} \end{aligned} + \begin{cases} 1) \text{ transformation to} \\ \text{achieve } \mathbf{u} \sim N(\mathbf{0}, \mathbf{I}) \\ \\ 2) \text{ procedure to get} \end{cases}$$

$\beta_{HL}$  approach



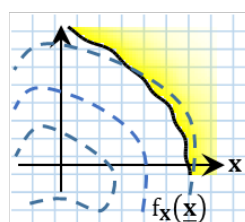
$$\mathbf{X} = \mathbf{D}\mathbf{L}\mathbf{u} + \mathbf{M}$$



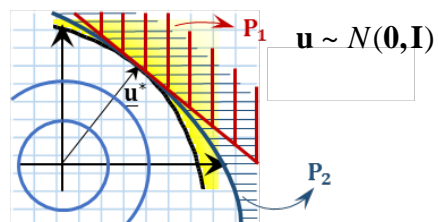
$$\beta_{HL} = \hat{\alpha} \mathbf{u}^*$$

$$\begin{cases} \mathbf{M}_u = \mathbf{0} \\ \sum_{uu} = \mathbf{I} \end{cases}$$

FORM/SORM



$$\mathbf{X} = \mathbf{T}(\mathbf{u})$$



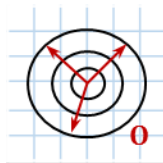
## ◎ Probability in the Uncorrelated Standard Normal Space

$$\mathbf{u} \sim N(\mathbf{0}, \mathbf{I}) \quad (\text{cf. } \mathbf{Z} \sim N(\mathbf{0}, \mathbf{R}))$$

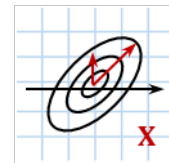
Joint PDF

$$\begin{aligned} \phi(\mathbf{u}) &= \frac{1}{(2\pi)^{n/2}} \exp\left(-\frac{1}{2}\|\mathbf{u}\|^2\right) \\ &= \prod_{i=1}^n \phi(u_i) \end{aligned}$$

where  $\phi(u_i) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{1}{2}u_i^2\right)$



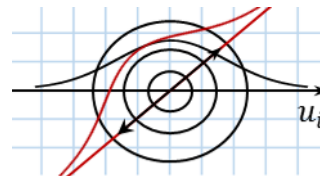
① Rotational Symmetry



~the probability density is completely defined by from origin

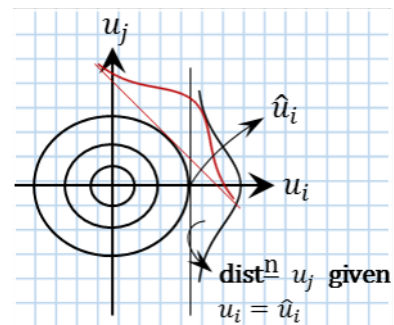
② Exponential Decay of Density

In r direction



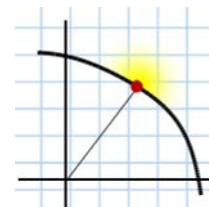
③ Exponential Decay of Density

In t direction



$\mathbf{u}^*$  : Richest point in terms of prob. density

Therefore, approximation around  $\mathbf{u}^*$  should be good



④ FORM : First Order Reliability Method