## A short course on

## Structural Reliability

This lecture:
FOSM \& FORM

Terje's Toolbox is freely available at terje.civil.ubc.ca
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## Reliability Methods

$$
\begin{gathered}
\text { Reliability }=1-p_{f} \\
p_{f}=\mathrm{P}(g \leq 0)=\int_{g \leq 0} \cdots \int f(\mathbf{x}) d \mathbf{x}
\end{gathered}
$$

| MCFOSM | $=$ mean-centred first-order second-moment method |
| :--- | :--- |
| FOSM | $=$ first-order second-moment method |
| FORM | $=$ first-order reliability method |
| SORM | $=$ second-order reliability method |
| MC | $=$ Monte Carlo sampling |
| IS | $=$ importance sampling |
| SS | $=$ subset sampling |
| DS | $=$ directional sampling |

## MCFOSM

$$
p_{f}=\mathrm{P}(g \leq 0)=\Phi\left(\frac{g-\mu_{g}}{\sigma_{g}}\right)=\Phi\left(-\frac{\mu_{g}}{\sigma_{g}}\right)=\Phi(-\beta) \quad\left(\text { Why seek } p_{f} \text { ? Appreciate } \beta!\right)
$$



## What is $\beta$ ?



## Invariance Problem

$$
\mu_{R}=30, \mu_{S}=20, \sigma_{R}=5, \sigma_{S}=10, \rho_{R S}=0.5
$$



## Univariate Explanation



## Solution

Linearizing nonlinear $g(\mathbf{x})$ at $\mathbf{x}=\mathbf{M}_{\mathrm{x}}$ causes the invariance problem

FOSM and FORM linearizes somewhere on the limit-state surface

To understand \& solve the issue:

Functions of random variables
Probability transformations

## Geometric Interpretation of $\beta$

Consider a linear limit-state function: $g(\mathbf{X})=a+\mathbf{b}^{T} \mathbf{X}$

Transform into a standardized space: $\mathbf{X}=\mathbf{M}_{X}+\mathbf{D}_{X} \mathbf{L Y}$

Resulting limit-state function (notice capital G): $G(\mathbf{Y})=a+\mathbf{b}^{T} \mathbf{M}_{X}+\mathbf{b}^{T} \mathbf{D}_{X} \mathbf{L Y}$

$$
=c+\mathbf{d}^{T} \mathbf{Y}
$$

$$
\text { MCFOSM: } \beta=\frac{\mu_{G}}{\sigma_{G}}=\frac{c}{\sqrt{\mathbf{d}^{T} \mathbf{d}}}=\frac{c}{\|\mathbf{d}\|}
$$

Distance from point to plane: $\Delta=\left|\frac{G(\mathbf{0})}{\|\nabla G\|}\right|=\left|\frac{c}{\|\mathbf{d}\|}\right| \longleftrightarrow$ Identical!

Original space:


MCFOSM:

$$
\begin{aligned}
& \beta_{1}=1.15 \\
& \beta_{2}=0.92
\end{aligned}
$$

## Visualization

$$
\mu_{R}=30, \mu_{S}=20, \sigma_{R}=5, \sigma_{S}=10, \rho_{R S}=0.5
$$

$$
\beta_{3}=1.13
$$



## Design Point



## Sequential Linearization

$$
G(\mathbf{y}) \approx G\left(\mathbf{y}_{m}\right)+\nabla G\left(\mathbf{y}_{m}\right)^{T} \cdot\left(\mathbf{y}-\mathbf{y}_{m}\right)=0
$$

$$
\Delta=\frac{G(\mathbf{0})}{\left\|\nabla G\left(\mathbf{y}_{m}\right)\right\|}=\frac{G\left(\mathbf{y}_{m}\right)-\nabla G\left(\mathbf{y}_{m}\right)^{T} \cdot \mathbf{y}_{m}}{\left\|\nabla G\left(\mathbf{y}_{m}\right)\right\|}=\frac{G\left(\mathbf{y}_{m}\right)}{\left\|\nabla G\left(\mathbf{y}_{m}\right)\right\|}+\boldsymbol{\alpha}^{T} \cdot \mathbf{y}_{m}
$$

$$
\mathbf{y}_{m+1}=-\Delta \cdot \frac{\nabla G\left(\mathbf{y}_{m}\right)}{\left\|\nabla G\left(\mathbf{y}_{m}\right)\right\|} \equiv \Delta \cdot \boldsymbol{\alpha}
$$

## Search Direction \& Step Size

$$
\begin{gathered}
\mathbf{y}_{m+1}=\mathbf{y}_{m}+s_{m} \cdot \mathbf{d}_{m} \\
\mathbf{d}_{m}=\mathbf{y}_{m+1}-\mathbf{y}_{m}=\left(\frac{G\left(\mathbf{y}_{m}\right)}{\left\|\nabla G\left(\mathbf{y}_{m}\right)\right\|}+\boldsymbol{\alpha}^{T} \cdot \mathbf{y}_{m}\right) \boldsymbol{\alpha}-\mathbf{y}_{m} \\
\text { Step size options: }\left\{\begin{array}{l}
s_{m}=1 \\
s_{m}=b^{k} \quad \text { (Armijo's rule, typically } b=0.5, k=0,1,2,3, \ldots \text { ) } \\
s_{m}=\text { Unidirectional optimization algorithm (golden section, etc.) }
\end{array}\right. \\
\end{gathered}
$$

## Convergence Criteria

$$
\begin{gathered}
\left|\frac{G\left(\mathbf{y}_{m}\right)}{G_{0}}\right| \leq e_{1} \\
\left\|\mathbf{y}_{m}-\left(\boldsymbol{\alpha}_{m}^{T} \mathbf{y}_{m}\right) \boldsymbol{\alpha}_{m}\right\| \leq e_{2}
\end{gathered}
$$



## Analysis Procedure

1. Set $m=1$
2. Select starting point in standard space: $\mathbf{y}_{m}$
3. Transform into original space: $\mathbf{y}_{m} \rightarrow \mathbf{x}_{m}$
4. Evaluate limit-state function $G\left(\mathbf{y}_{m}\right)=g\left(\mathbf{x}_{m}\right)$
5. Evaluate gradient of limit-state function: $\frac{\partial G}{\partial \mathbf{y}}=\frac{\partial g}{\partial \mathbf{u}} \frac{\partial \mathbf{u}}{\partial \mathbf{x}} \frac{\partial \mathbf{x}}{\partial \mathbf{y}}$
6. If $m=1$, set scaling factor for first convergence criterion: $G_{0}=G\left(\mathbf{y}_{m}\right)$
7. Check convergence: $\left|\frac{G\left(\mathbf{y}_{m}\right)}{G_{0}}\right| \leq e_{1} \quad\left\|\mathbf{y}_{m}-\left(\boldsymbol{\alpha}_{m}^{T} \mathbf{y}_{m}\right) \boldsymbol{\alpha}_{m}\right\| \leq e_{2}$
8. If convergence is NOT achieved, go back to Step 3 with: $\mathbf{y}_{m+1}=\mathbf{y}_{m}+s_{m} \cdot \mathbf{d}_{m}$
9. If convergence is achieved: $\quad \beta=\left\|\mathbf{y}^{*}\right\| \quad p_{f}=\Phi(-\beta)$

## Evolution of the Search





More slides to come here...

More lectures:

Terje's Toobox:
terje.civil.ubc.ca

