

Simulation methods for analysis and design in stochastic linear dynamics

Marcos Valdebenito¹
¹TU Dortmund, Germany



Michael Beer



Matthias Faes



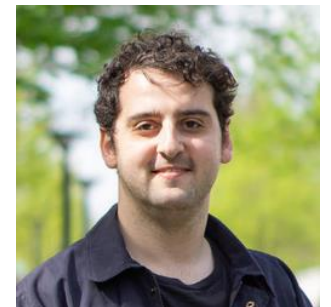
Héctor Jensen



Danko Jerez

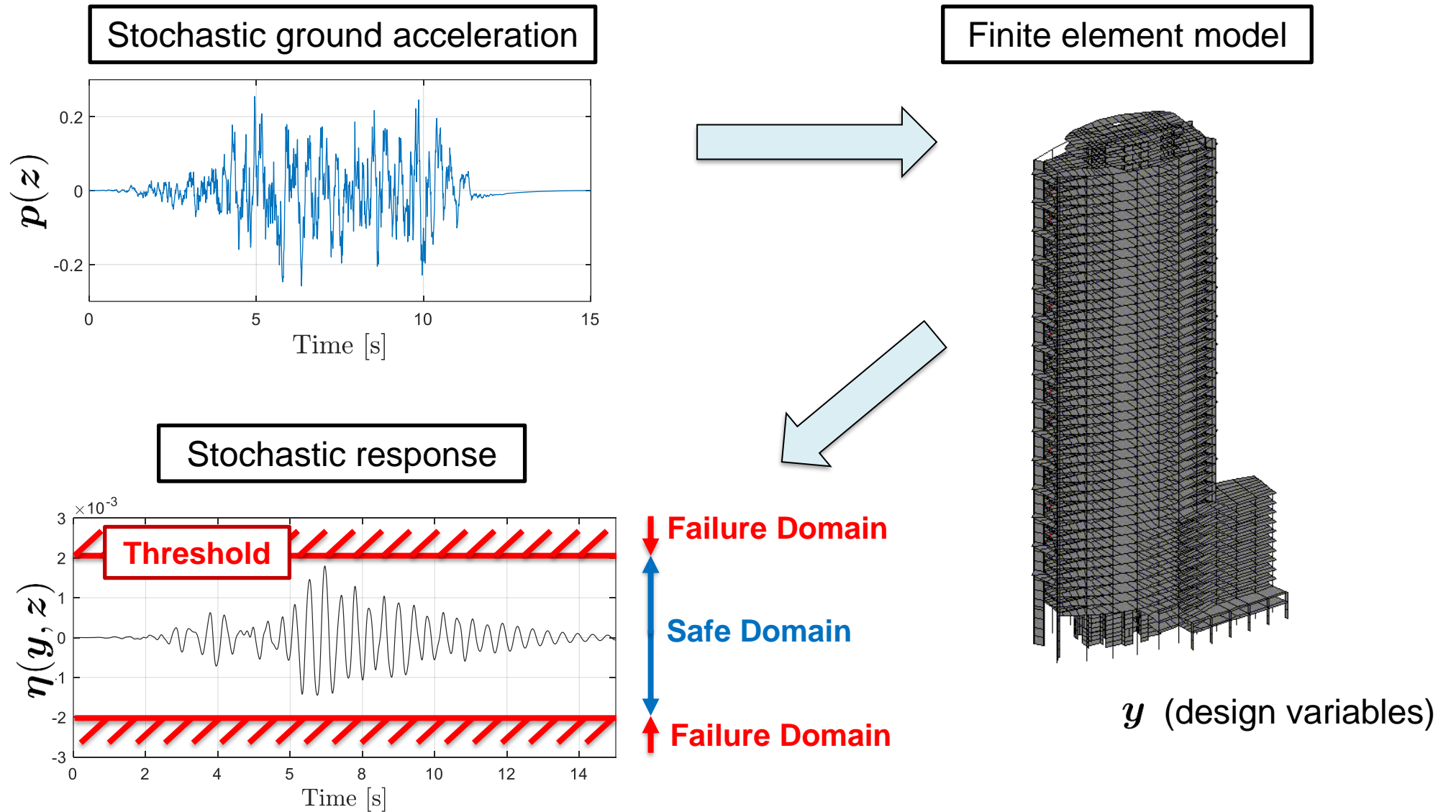


Franco Mayorga

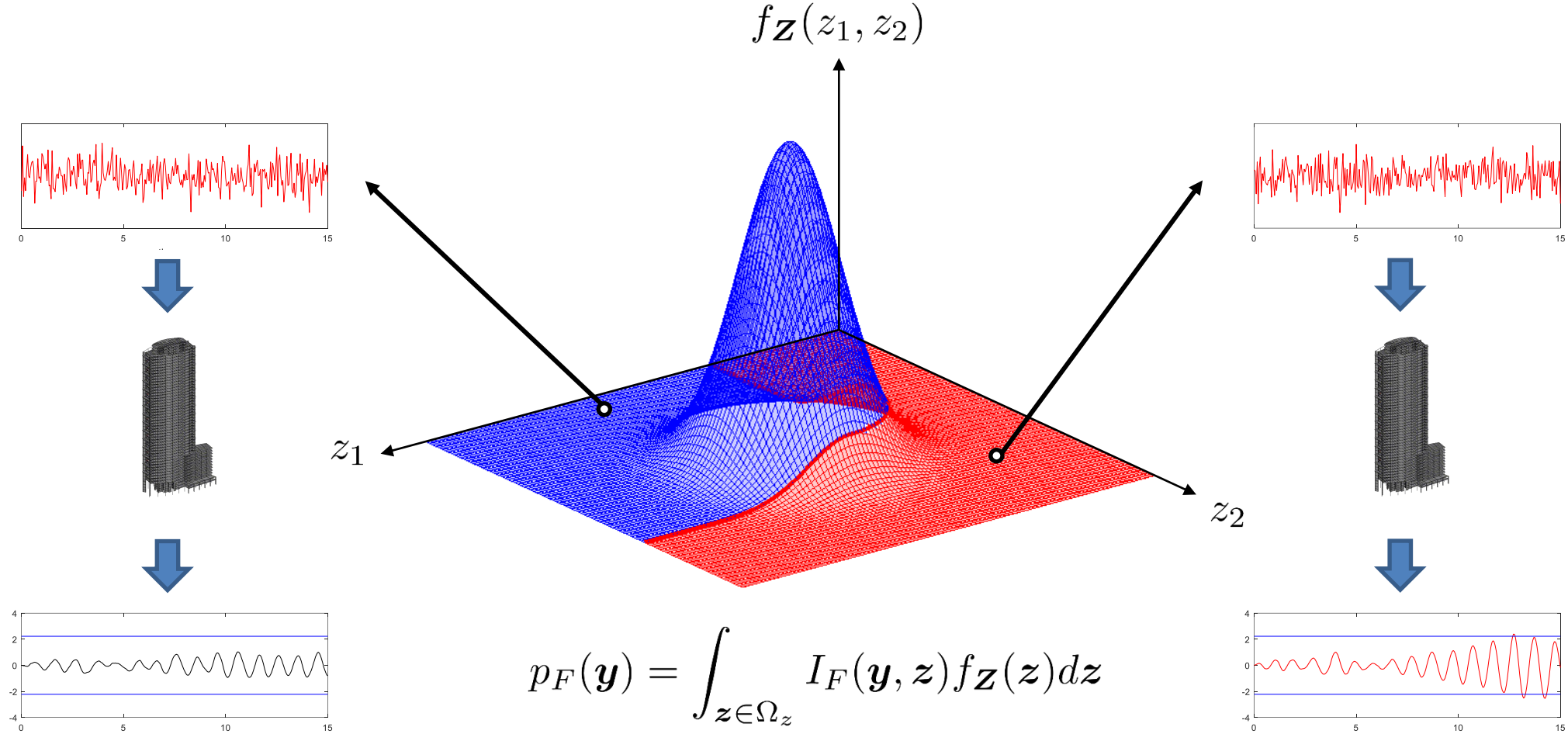


Mauricio Misraji

Motivation

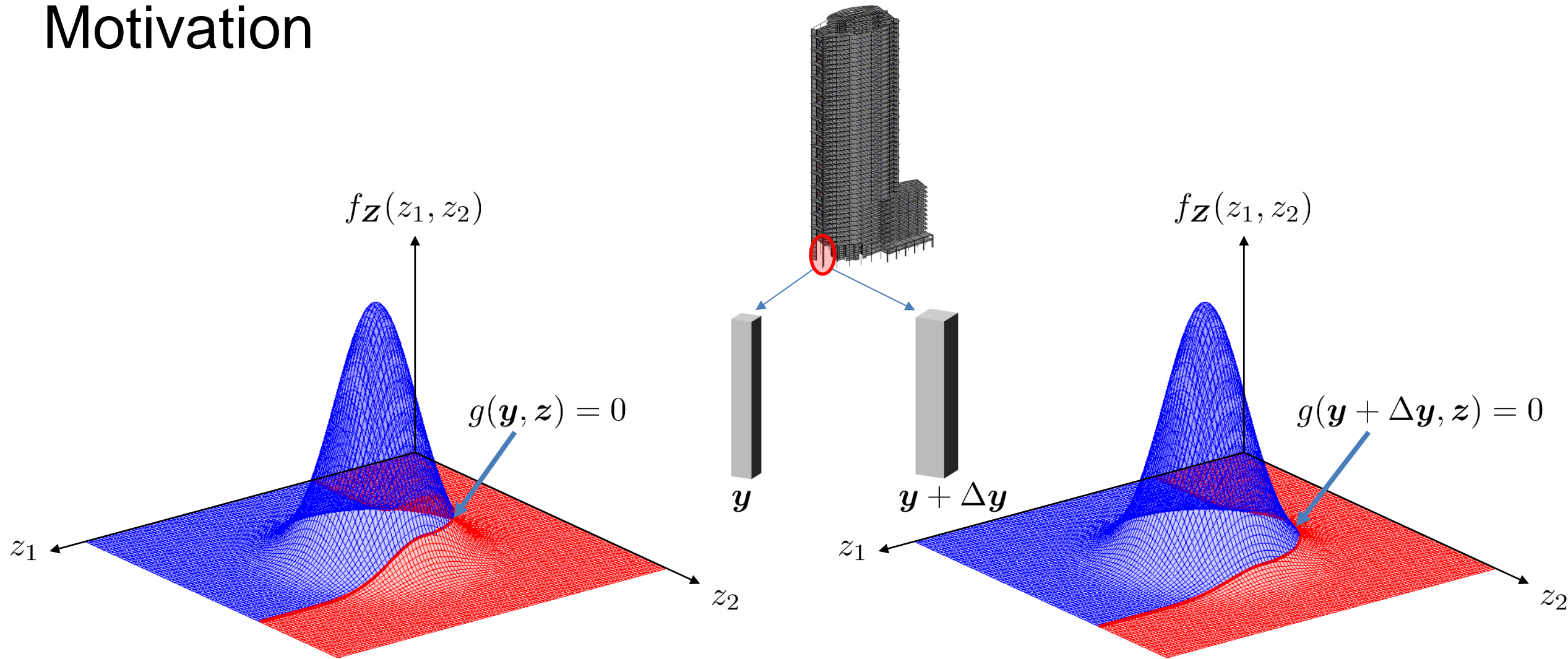


Motivation



Challenge 1: probability estimation (dimensionality, non-Gaussianity, multiple failure domains, nonlinearities)

Motivation

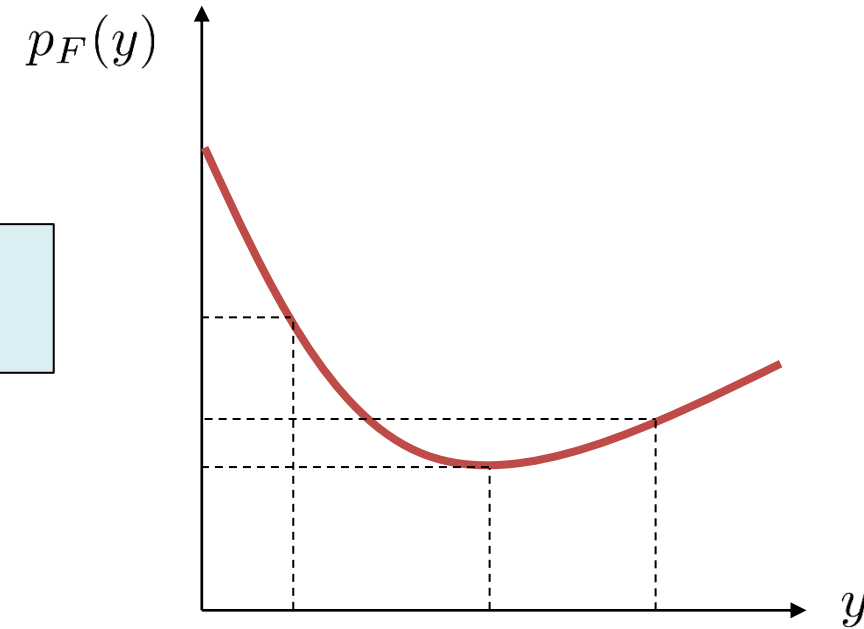
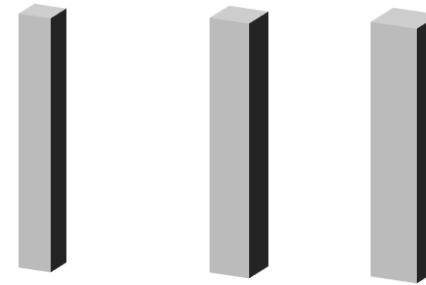
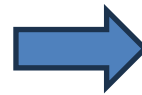


$$\frac{\partial p_F(\mathbf{y})}{\partial y_j} = \frac{\partial}{\partial y_j} \left(\int_{\mathbf{z} \in \Omega_z} I_F(\mathbf{y}, \mathbf{z}) f_{\mathbf{Z}}(\mathbf{z}) d\mathbf{z} \right)$$

Challenge 2: sensitivity

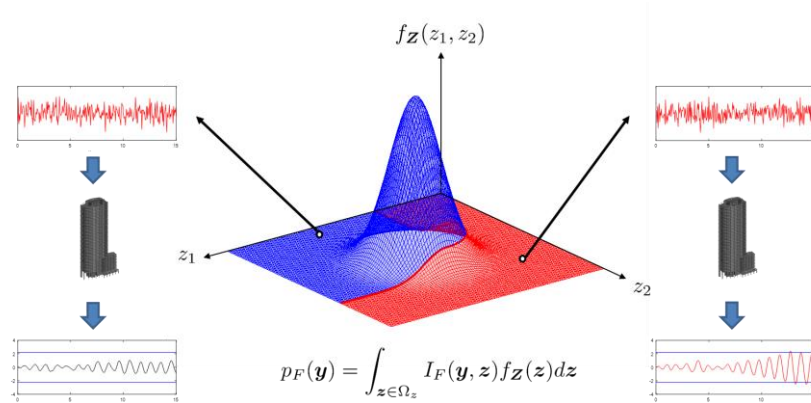
Motivation

Challenge 3: optimal design

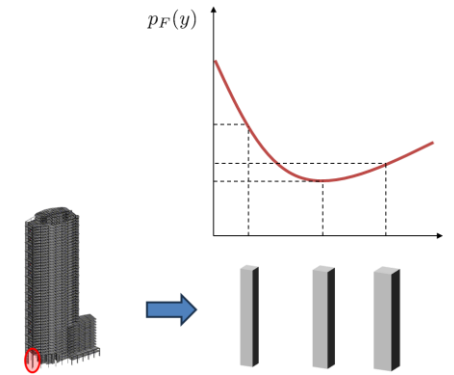


Motivation

Challenge 1 & 2: probability and sensitivity



Challenge 3: optimal design



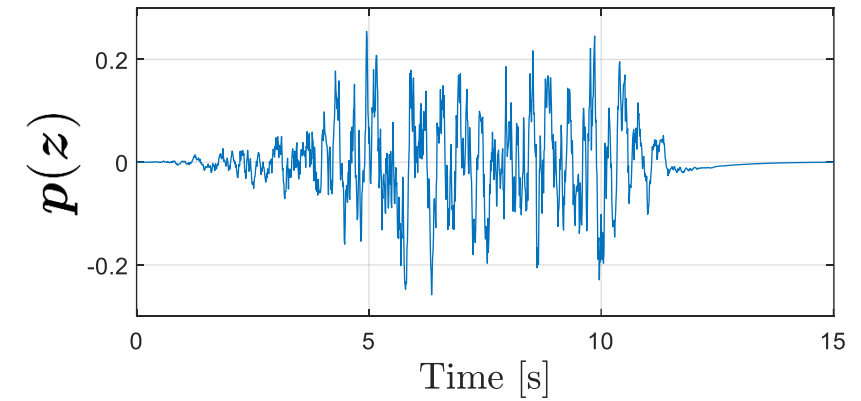
Focus:

- Linear structural systems
- Gaussian stochastic loading

Challenge 1: Failure Probability

- Stochastic loading modelled as Gaussian process
(assumption: $\mu = \mathbf{0}$)

$$p(z) = \mu + Bz$$



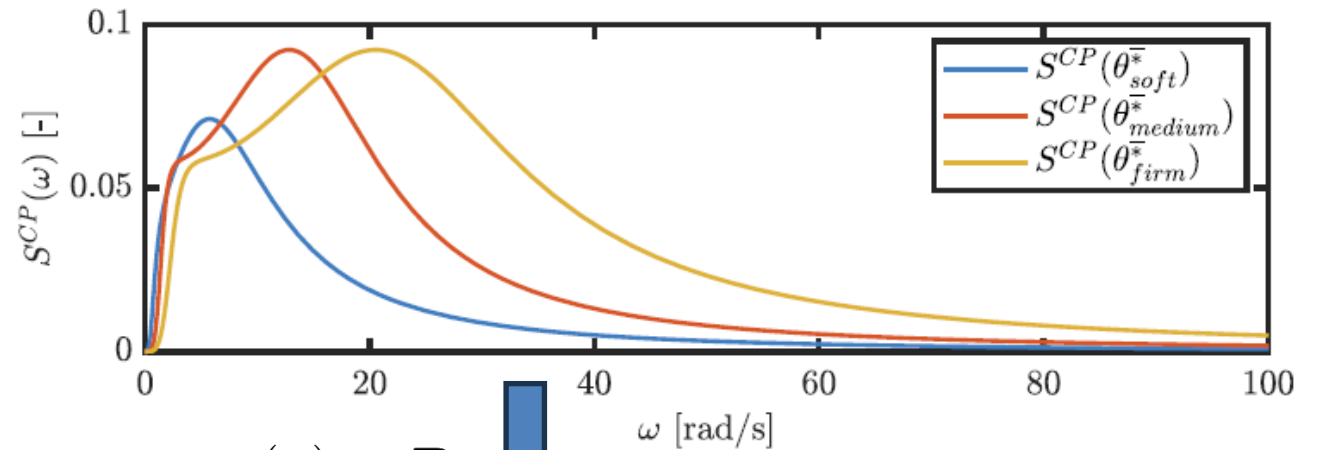
$$\left[\begin{array}{c} \text{Stochastic loading} \end{array} \right] = \left[\begin{array}{c} \text{Mean} \end{array} \right] + \left[\begin{array}{c} \text{Mode 1} \\ \text{Mode 2} \\ \vdots \\ \text{Mode N} \end{array} \right] \times \left[\begin{array}{c} \text{Response 1} \\ \text{Response 2} \\ \vdots \\ \text{Response N} \end{array} \right]$$

Challenge 1: Failure Probability

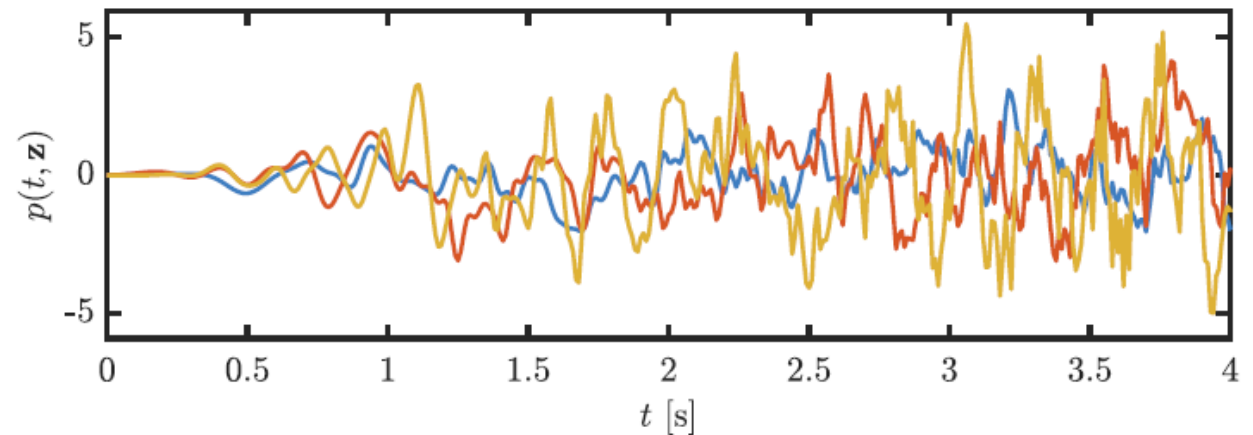
- Stochastic loading: Clough-Penzien power spectrum

$$S^{CP}(\omega) = \frac{\omega_g^4 + (2\zeta_g\omega_g\omega)^2}{(\omega_g^2 - \omega^2)^2 + (2\zeta_g\omega_g\omega)^2} \cdot \frac{\omega^4}{(\omega_f^2 - \omega^2)^2 + (2\zeta_f\omega_f\omega)^2} \cdot S_0$$

Soil type	ω_g [rad/s]	ζ_g	ω_f [rad/s]	ζ_f
Firm	8π	0.60	0.8π	0.60
Medium	5π	0.60	0.5π	0.60
Soft	2.4π	0.85	0.24π	0.85

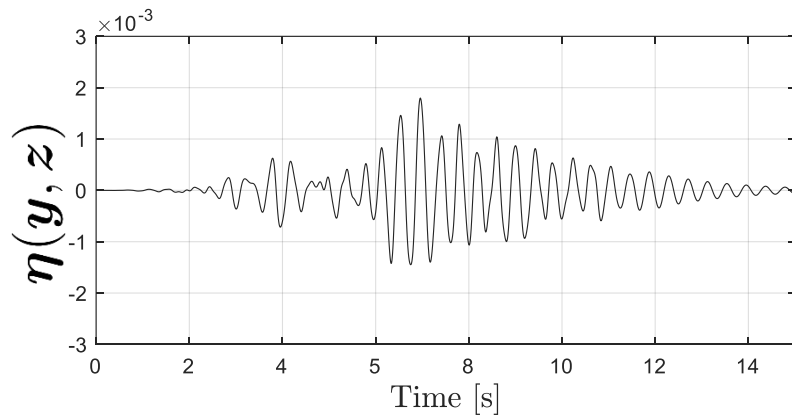
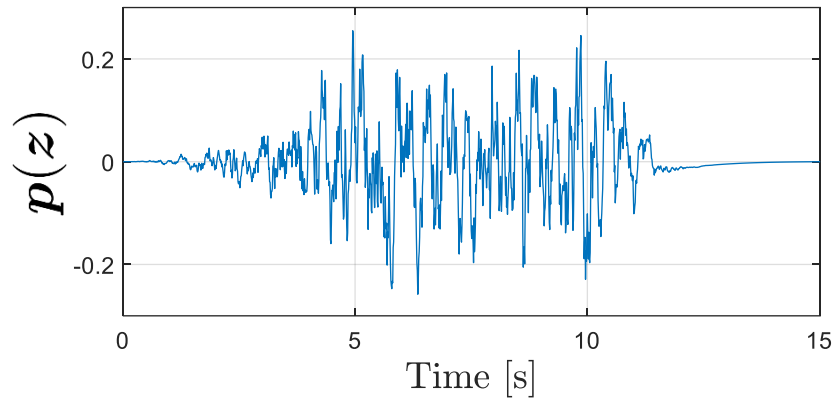


$$p(z) = Bz$$

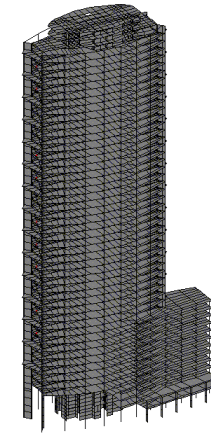


Challenge 1: Failure Probability

- Structural response: convolution integral



$$p(z) = Bz$$



Finite element model

y (design variables)

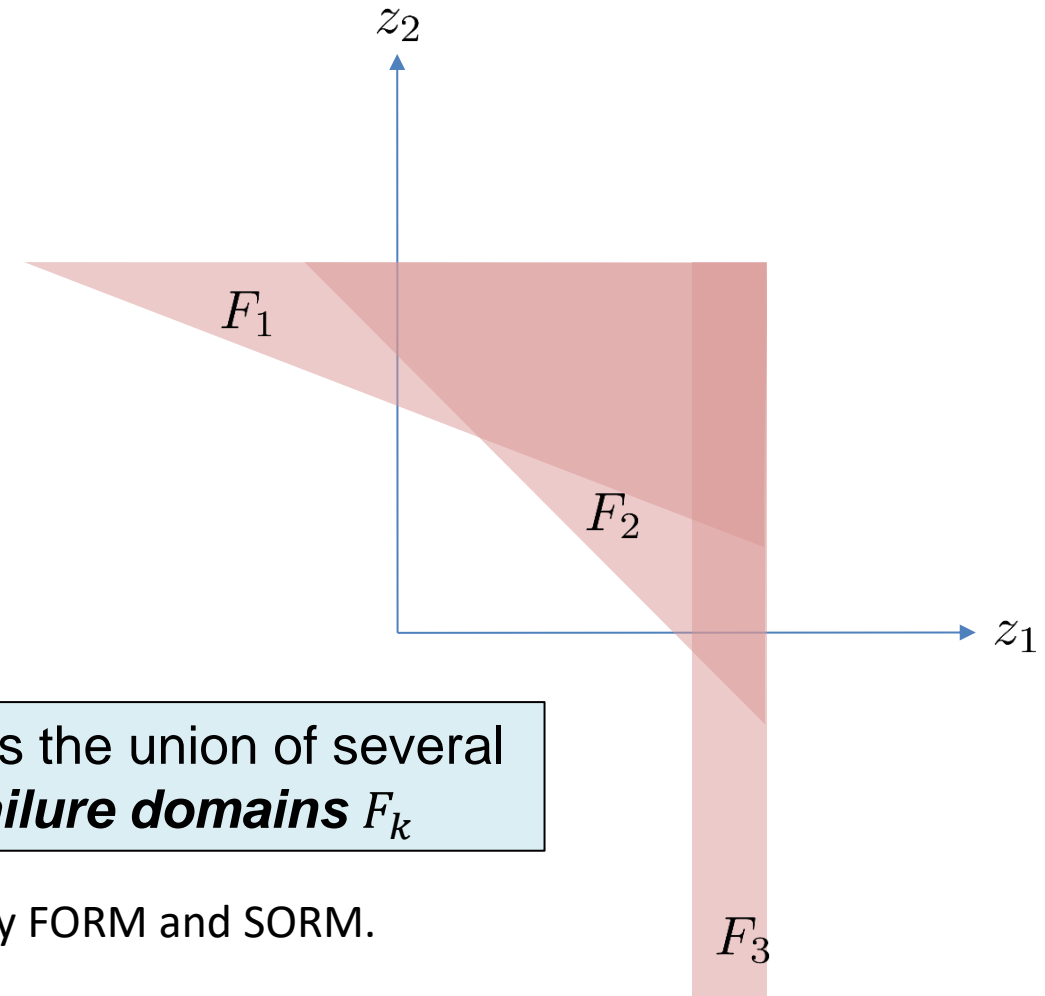
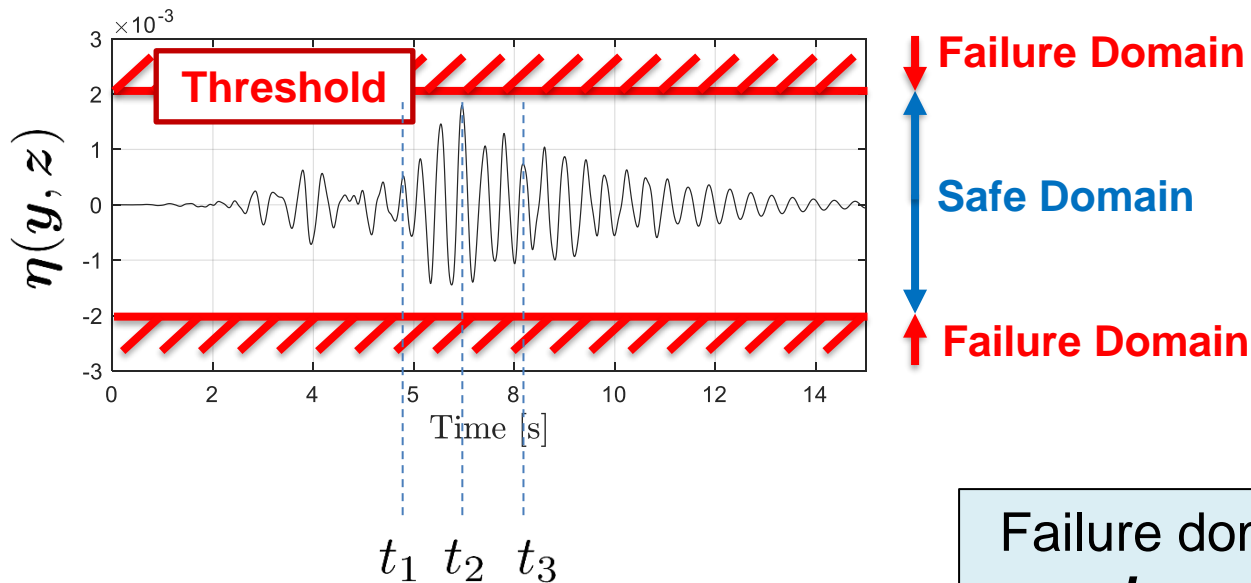
$$\eta(t, y, z) = \int_0^t h(y, t - \tau) p(\tau, z) d\tau$$

$$\eta(y, z) = \underbrace{H(y)}_{\text{spectral properties}} \underbrace{Bz}_{\text{loading}} = A(y)z$$

Challenge 1: Failure Probability

- Geometry of the failure domain* in stochastic linear dynamics under Gaussian force

$$\eta(\mathbf{y}, \mathbf{z}) = \mathbf{A}(\mathbf{y})\mathbf{z}$$



Failure domain F is the union of several **elementary failure domains** F_k

*Der Kiureghian, A. The geometry of random vibrations and solutions by FORM and SORM. Probabilistic Engineering Mechanics, 2000 , 15 , 81-90

Challenge 1: Failure Probability

- Geometry of the failure domain in stochastic linear dynamics under Gaussian force

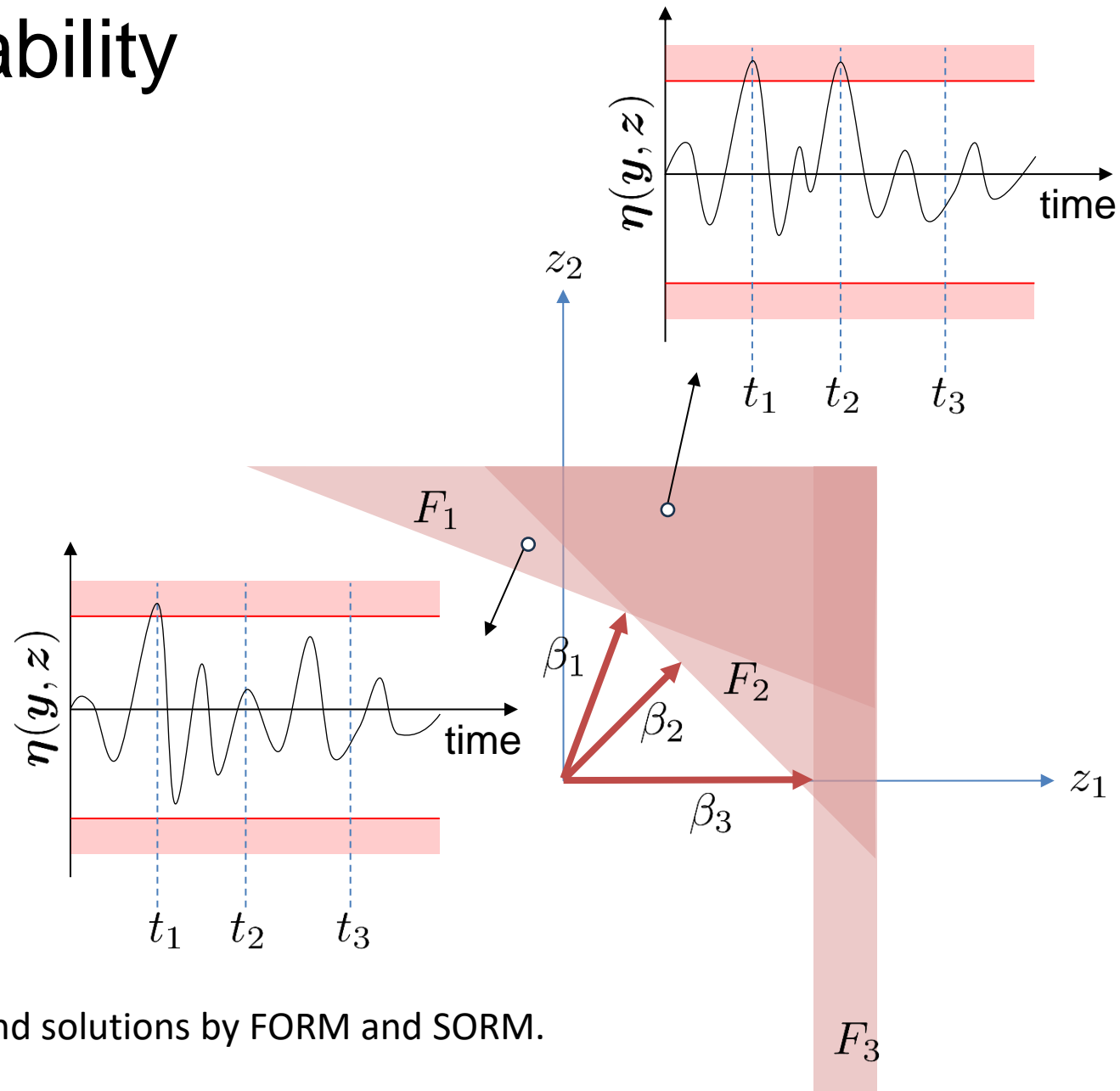
- Reliability for elementary failure domain known in closed form

$$P[F_k] = \Phi(-\beta_k)$$

- Bounds for failure probability*

$$p_F \leq \hat{P}_F = \Phi(-\beta_1) + \Phi(-\beta_2) + \Phi(-\beta_3)$$

Upper bound, ignores **interactions**



*Der Kiureghian, A. The geometry of random vibrations and solutions by FORM and SORM. Probabilistic Engineering Mechanics, 2000 , 15 , 81-90

Challenge 1: Failure Probability

- **Coordinate change** of the failure probability integral and **importance sampling density function**

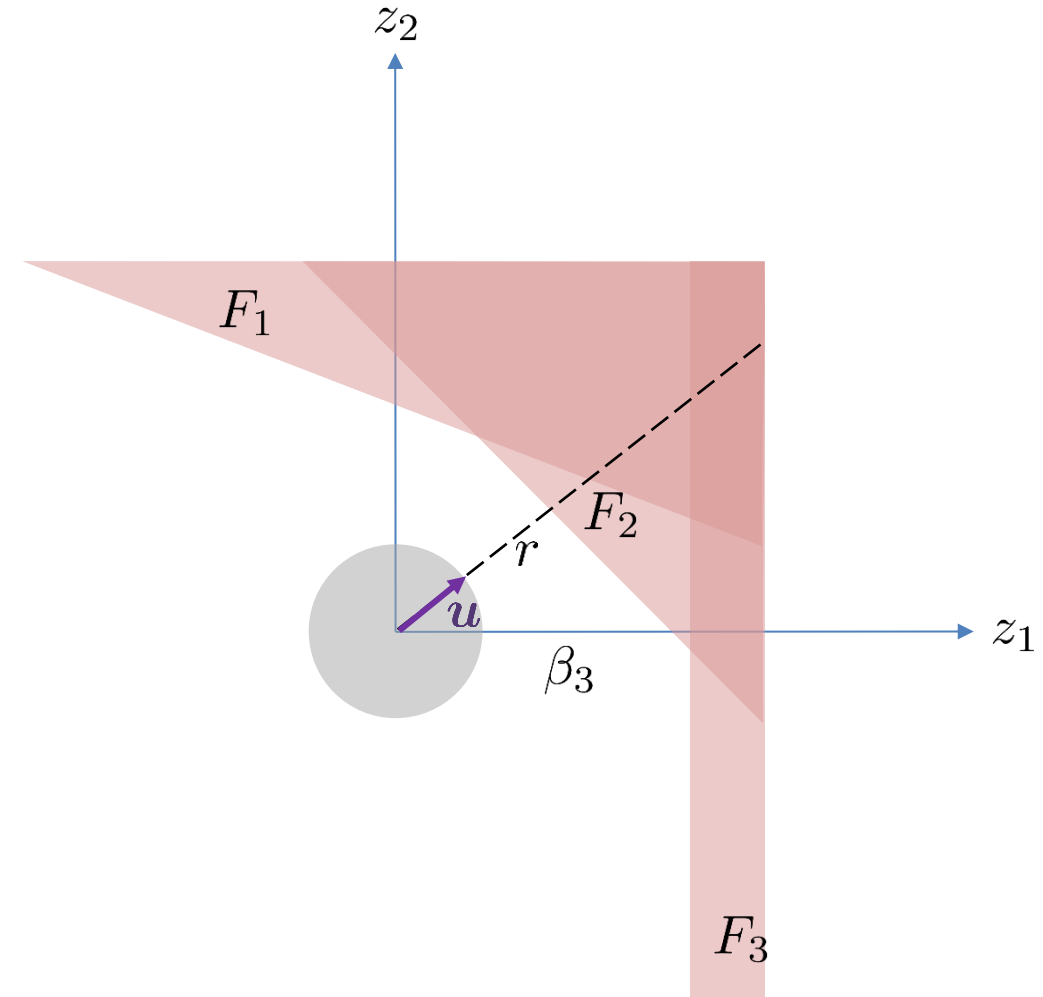
$$p_F(\mathbf{y}) = \int_{\mathbf{z} \in \Omega_z} I_F(\mathbf{y}, \mathbf{z}) f_{\mathbf{Z}}(\mathbf{z}) d\mathbf{z}$$



$$p_F = \int_{\mathbf{u} \in \Omega_U} \int_0^\infty 2r I_F(\mathbf{y}, r\mathbf{u}) f_{R^2}(r^2) f_U(\mathbf{u}) dr d\mathbf{u}$$



$$p_F = \int_{\mathbf{u} \in \Omega_U} \int_0^\infty 2r I_F(\mathbf{y}, r\mathbf{u}) f_{R^2}(r^2) \frac{f_U(\mathbf{u})}{f_U^{\text{IS}}(\mathbf{u})} f_U^{\text{IS}}(\mathbf{u}) dr d\mathbf{u}$$

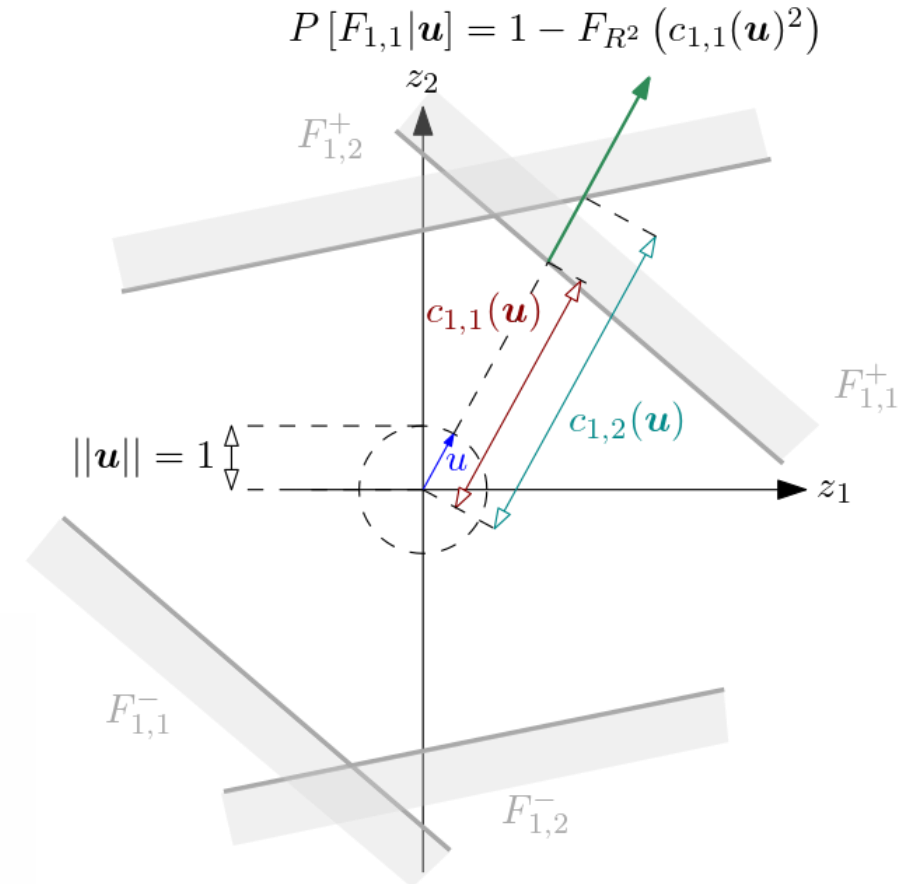
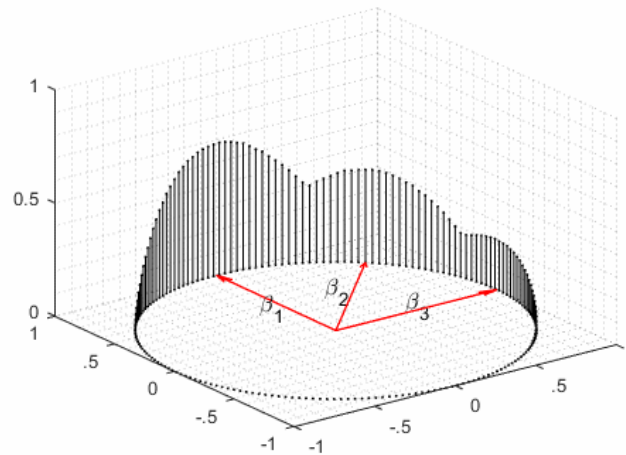
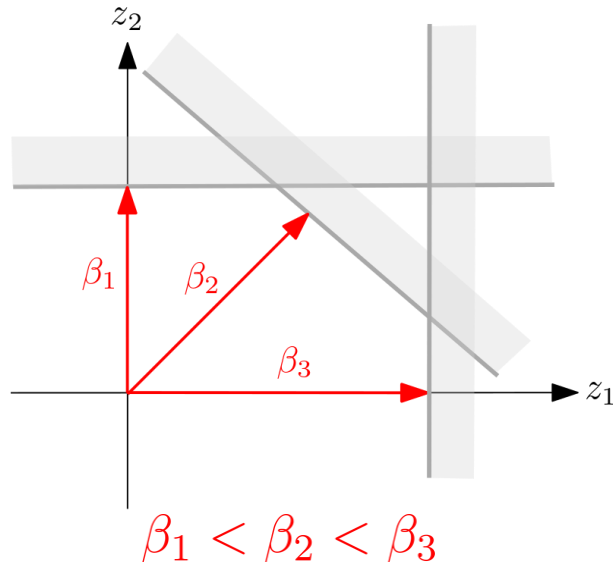


Challenge 1: Failure Probability

- Importance sampling density function**

$$f_U^{IS}(\mathbf{u}) = \sum_{i=1}^{n_\eta} \sum_{k=1}^{n_T} w_{i,k} f_U(\mathbf{u}/F_{i,k})$$

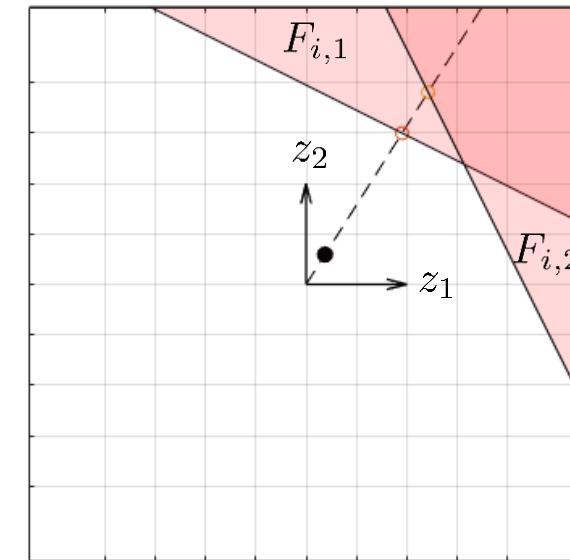
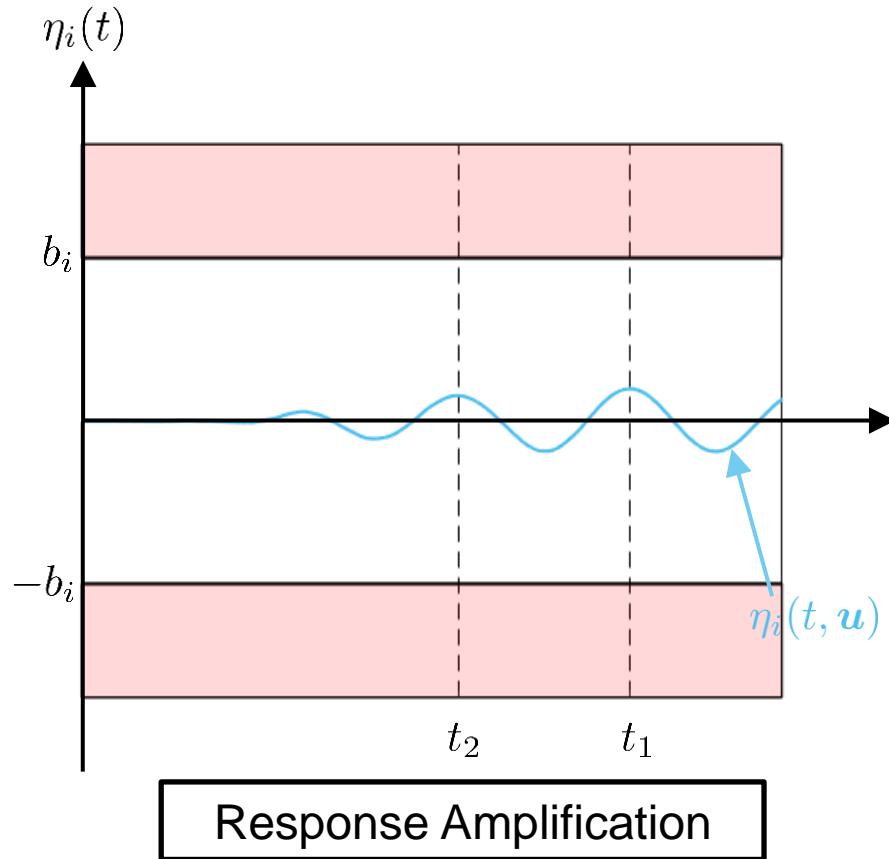
$$= \frac{f_U(\mathbf{u})}{\hat{P}_F} \sum_{i=1}^{n_\eta} \sum_{k=1}^{n_T} \left(1 - F_{R^2} \left(c_{i,k}(\mathbf{u})^2 \right) \right)$$



*O. Ditlevsen, P. Bjerager, R. Olesen, and A. M. Hasofer, "Directional simulation in Gaussian processes," Probabilistic Engineering Mechanics, vol. 3, Art. no. 4, 1988.

Challenge 1: Failure Probability

- Interpretation of distances $c_{i,k}$



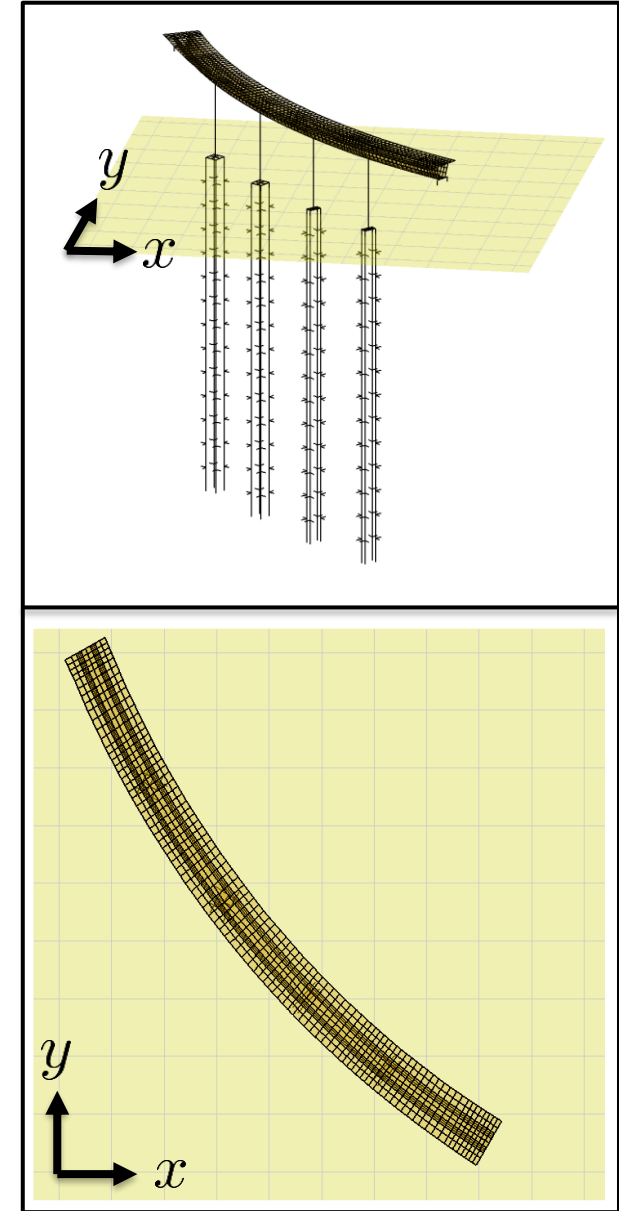
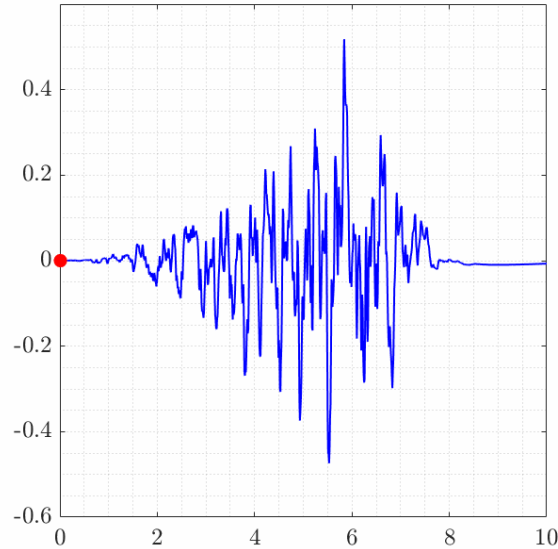
$$\tilde{p}_F^{\text{DIS}} \approx \hat{P}_F \left(\frac{1}{N} \sum_{j=1}^N \frac{1 - f_{R^2} \left(c_{\min} \left(\mathbf{u}^{(j)} \right)^2 \right)}{\sum_{i=1}^{n_\eta} \sum_{k=1}^{n_T} 1 - f_{R^2} \left(c_{i,k} \left(\mathbf{u}^{(j)} \right)^2 \right)} \right)$$

Upper bound

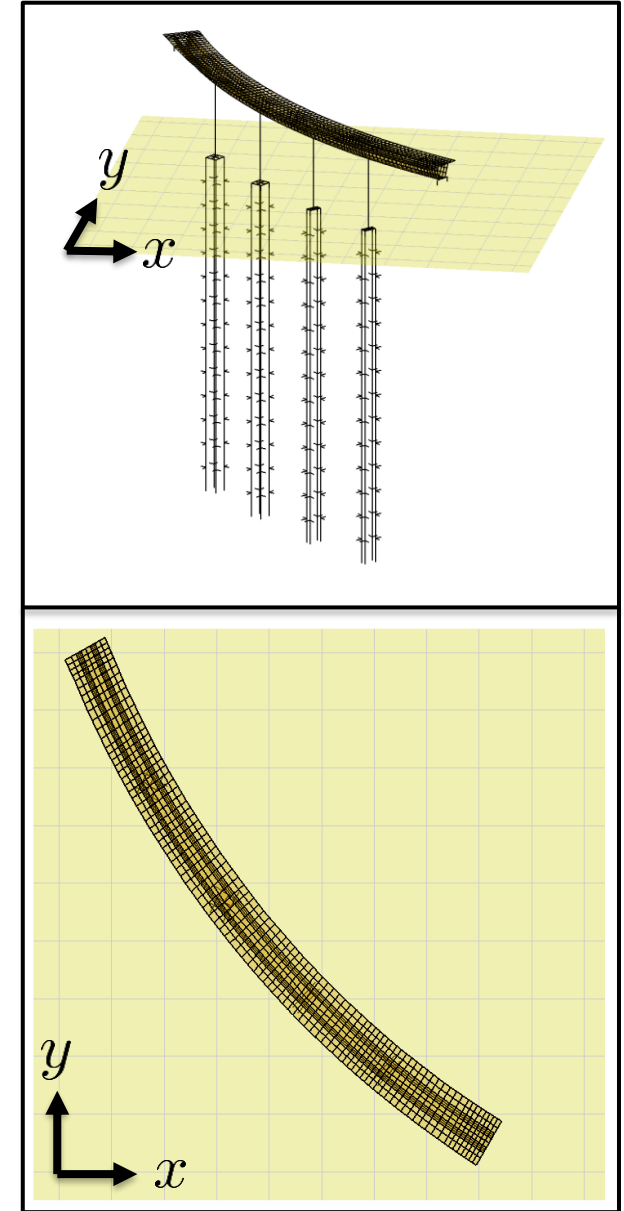
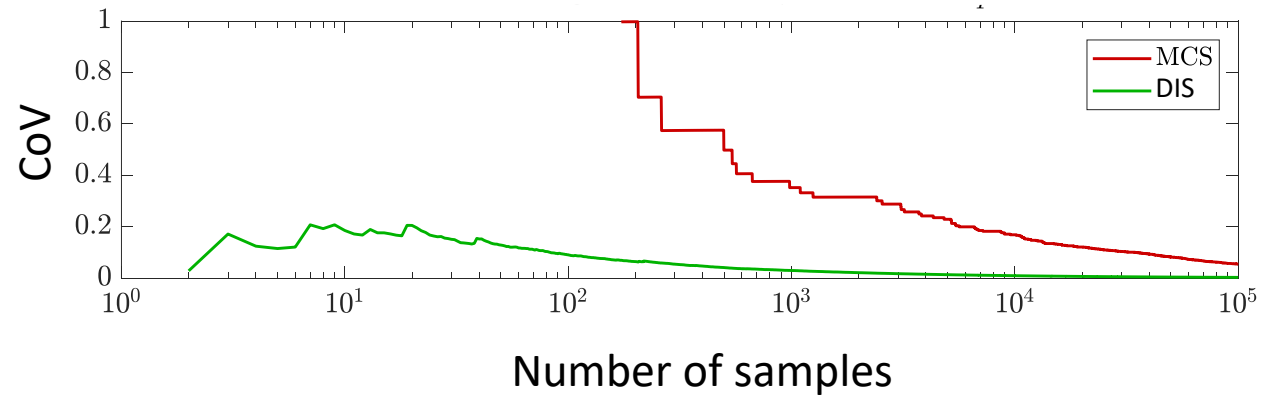
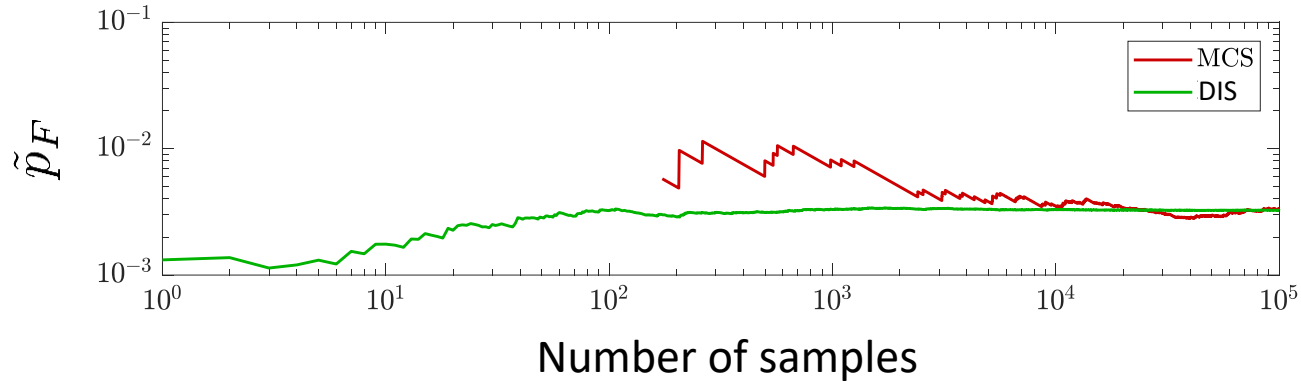
Value between 0 and 1, overlap

Challenge 1: Failure Probability

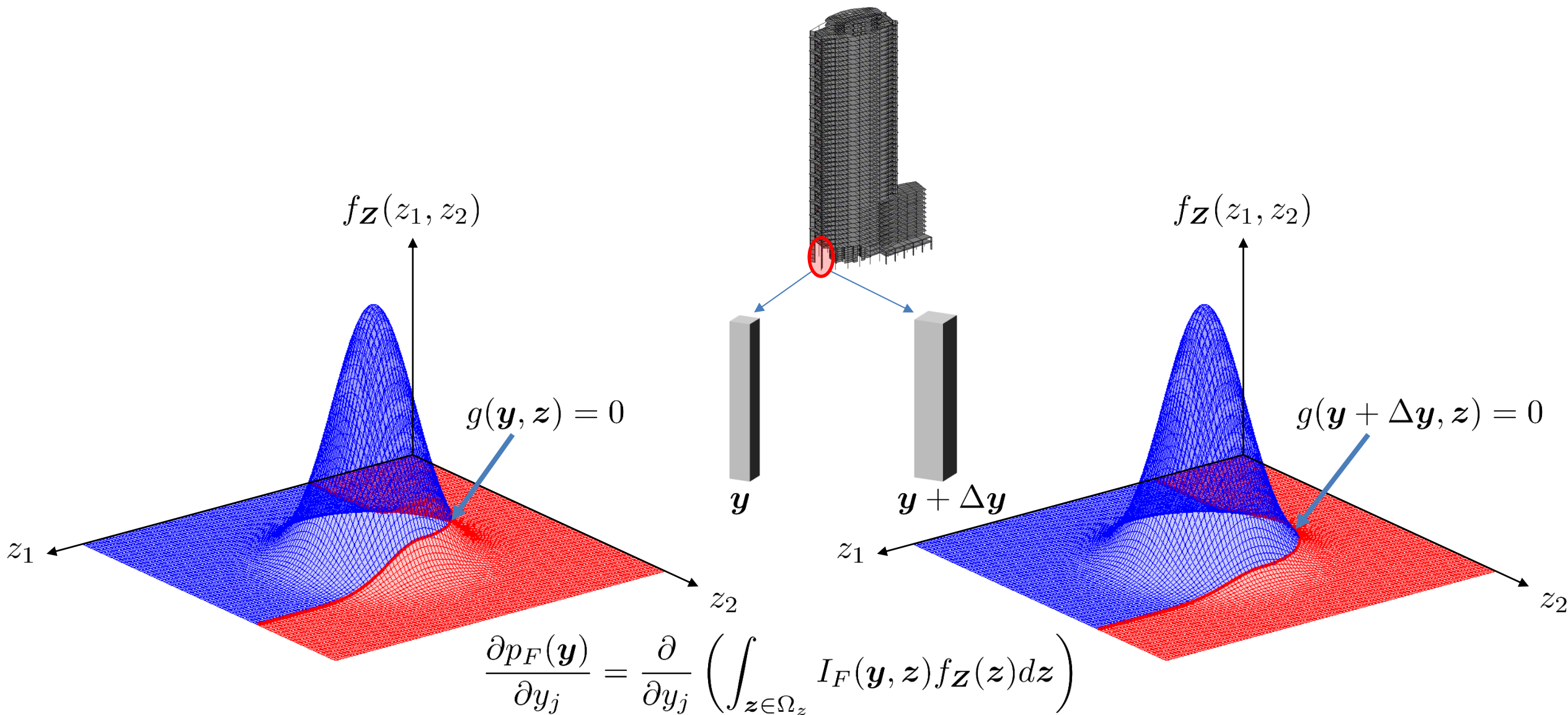
- Example:
 - Bridge subjected to stochastic ground acceleration, low vibration level, linear elastic range.
 - FE model involves **10068** DOF's
- Response of interest: first excursion, column drift (8 responses of interest)
- Uncertainty:
 - Stochastic acceleration comprises **1001 random variables**
 - Discrete time representation involves **8008 elementary failure domains**
- Objective: Calculate first excursion probability



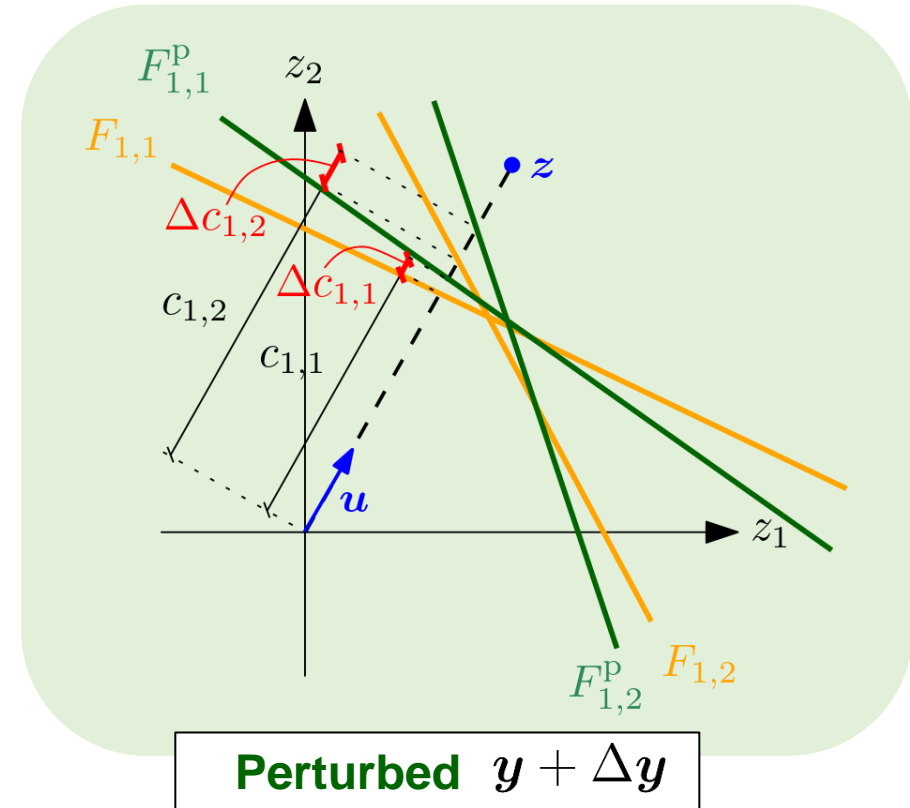
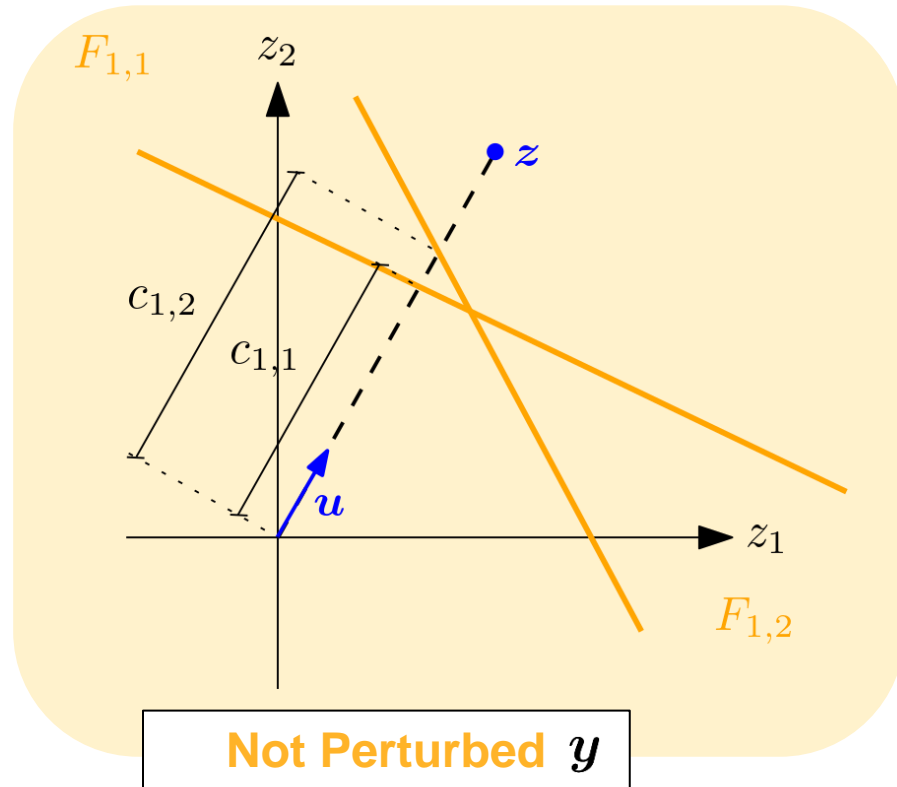
Challenge 1: Failure Probability



Challenge 2: Probability Sensitivity



Challenge 2: Probability Sensitivity

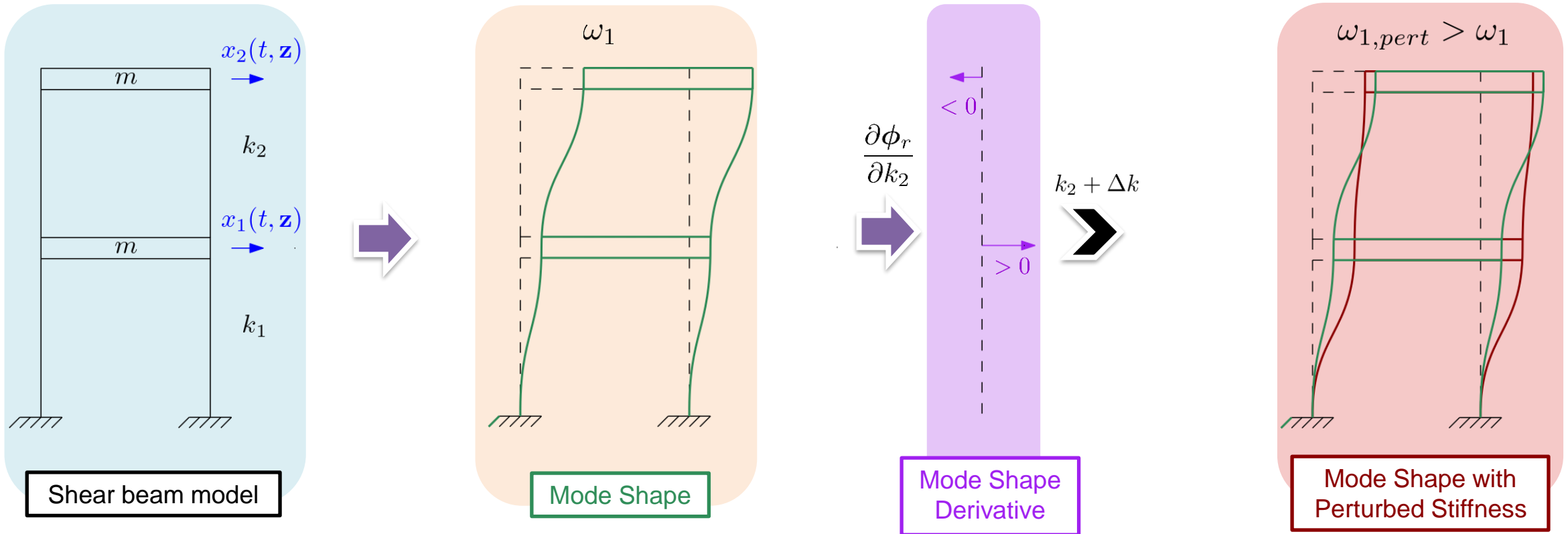


$$\Rightarrow \frac{\partial \tilde{p}_F^{\text{DIS}}}{\partial y_q} \approx -\frac{2\hat{P}_F}{N} \left(\frac{\sum_{j=1}^N \frac{f_{R^2} \left(c_{\min}(\mathbf{y}, \mathbf{u}^{(j)})^2 \right) c_{\min}(\mathbf{y}, \mathbf{u}^{(j)}) \frac{\partial c_{\min}(\mathbf{y}, \mathbf{u}^{(j)})}{\partial y_q}}{\sum_{i=1}^{n_\eta} \sum_{k=1}^{n_T} 1 - f_{R^2} \left(c_{i,k}(\mathbf{y}, \mathbf{u}^{(j)})^2 \right)} \right)$$

Challenge 2: Probability Sensitivity

- Sensitivity of spectral properties*

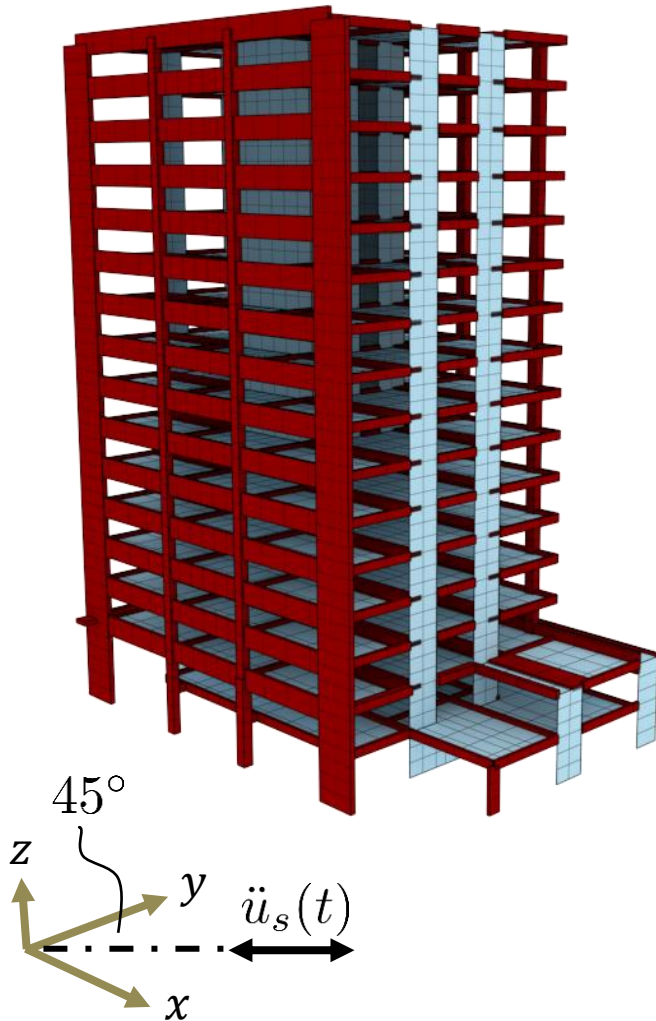
$$\begin{pmatrix} \mathbf{K} - \omega_r^2 \mathbf{M} & -\mathbf{M} \phi_r \\ -\phi_r^T \mathbf{M} & 0 \end{pmatrix} \begin{pmatrix} \frac{\partial \phi_r}{\partial y_q} \\ \frac{\partial \omega_r}{\partial y_q} \end{pmatrix} = \begin{pmatrix} -\left(\frac{\partial \mathbf{K}}{\partial y_q} - \omega_r^2 \frac{\partial \mathbf{M}}{\partial y_q} \right) \\ 0.5 \phi_r^T \frac{\partial \mathbf{M}}{\partial y_q} \phi_r \end{pmatrix}$$



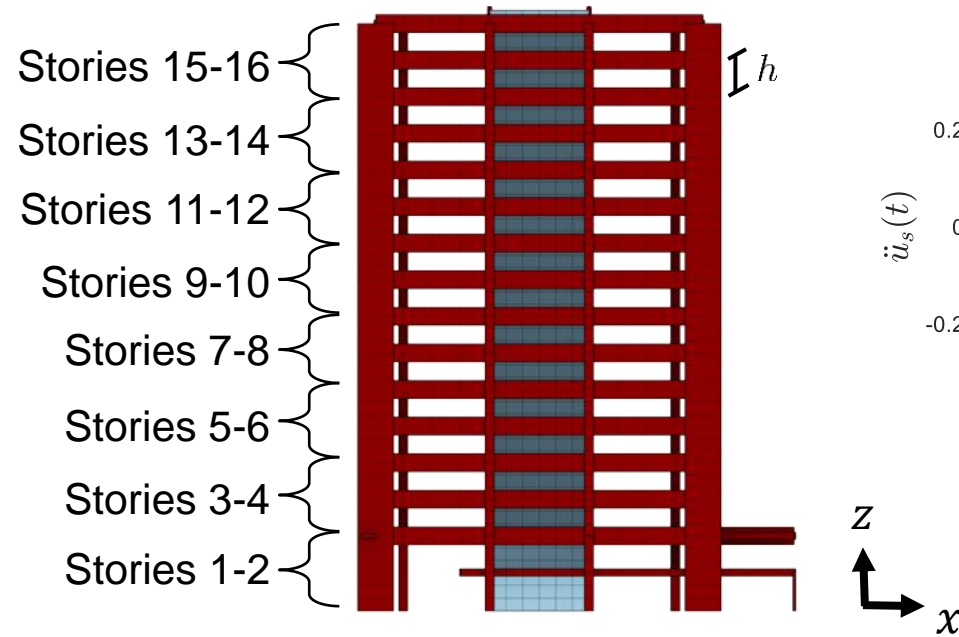
*I.-W. Lee and G.-H. Jung. An efficient algebraic method for the computation of natural frequency and mode shape sensitivity – part I, Distinct natural frequencies. *Computers & Structures*, 63(3):429-435.1997

Challenge 2: Probability Sensitivity

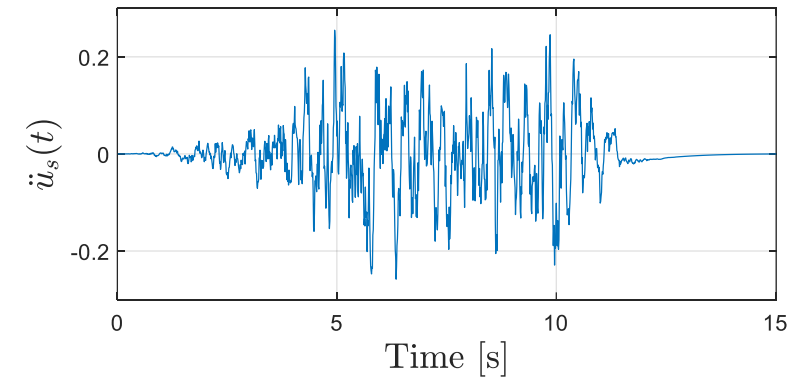
Perspective view



Elevation view

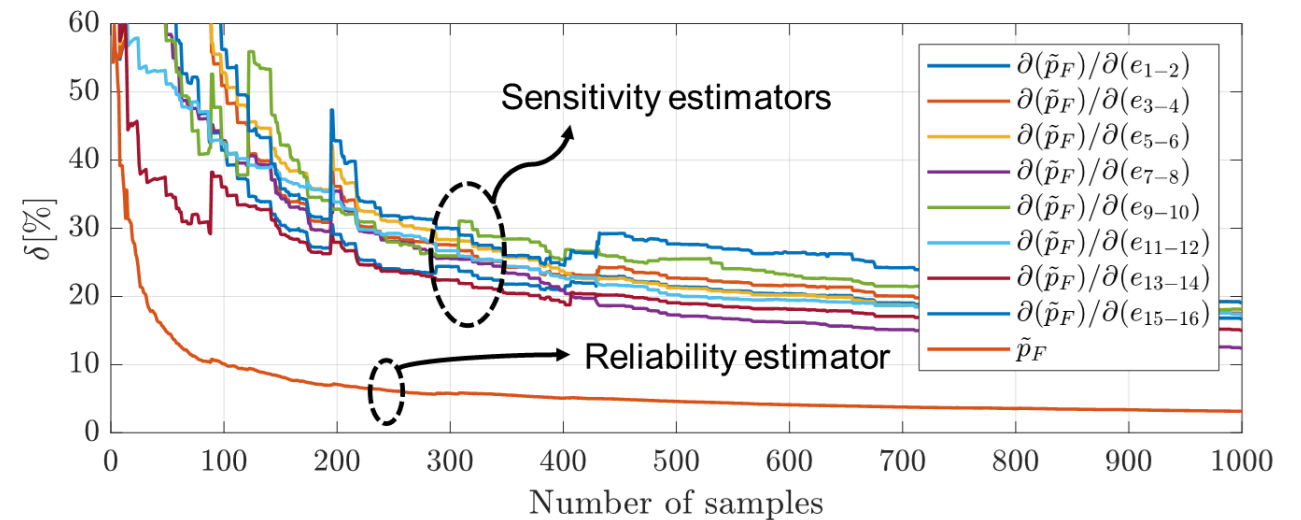
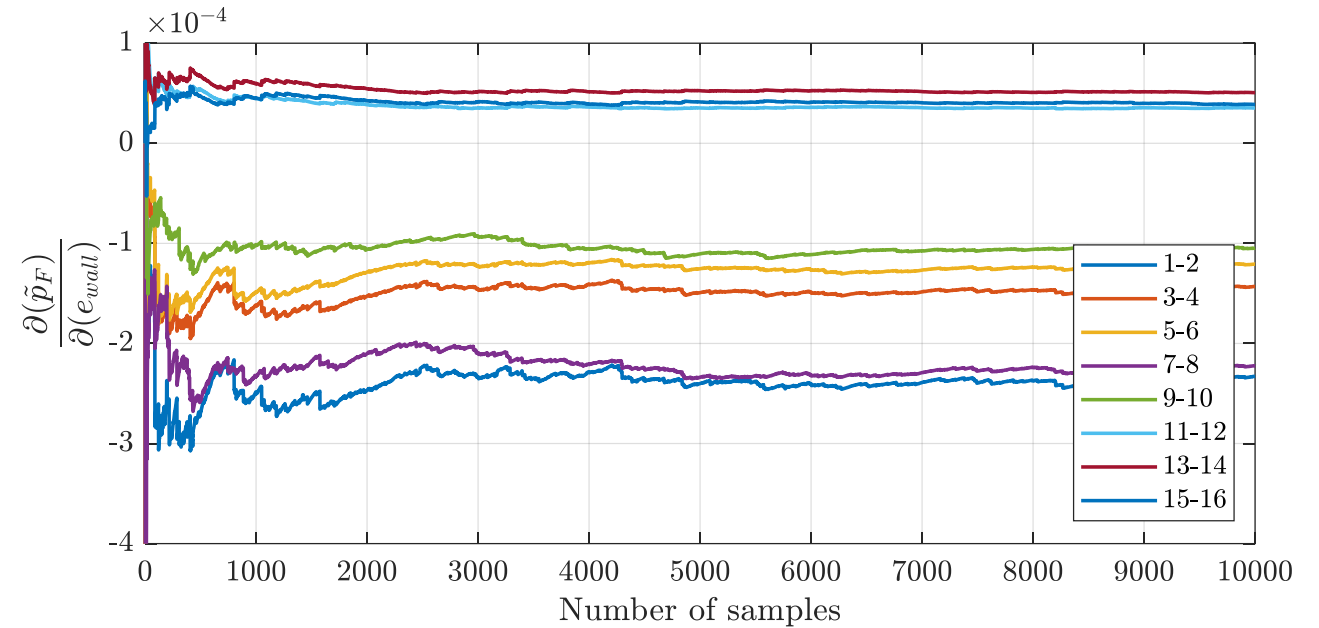
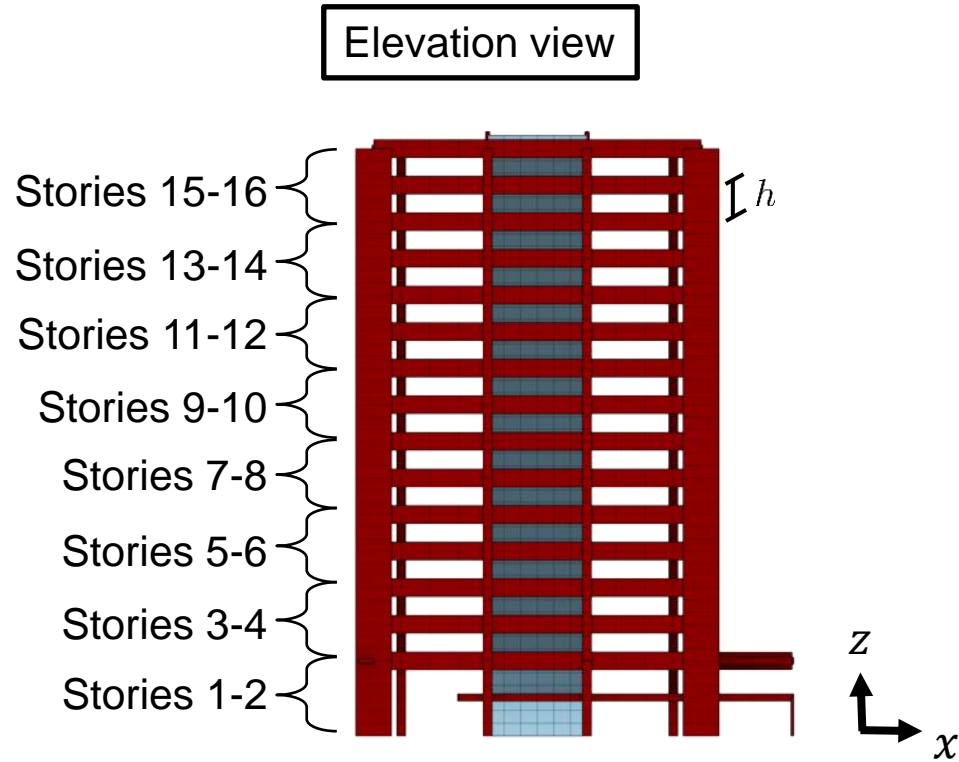


Realization of stochastic load



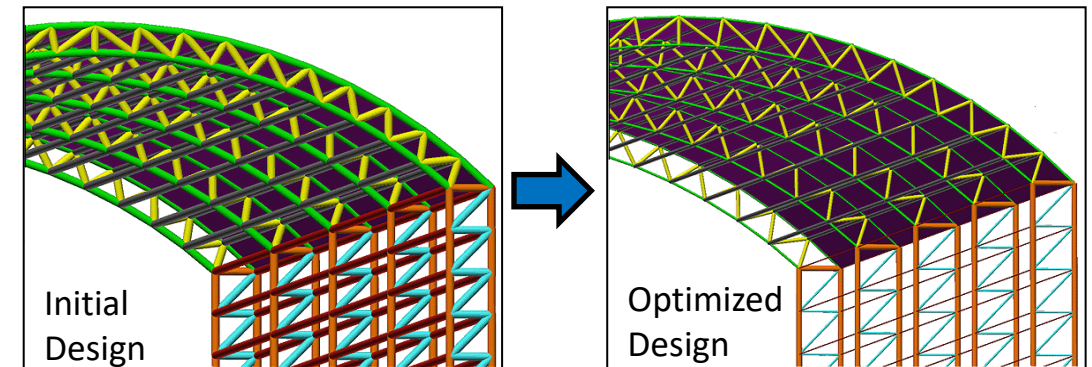
- ~ 30,000 DOFS, uncertain ground acceleration: discrete **filtered white noise**, 1001-time instants
- Failure criterion: Story drifts exceeds threshold in dir. x or y
- Objective: Calculate first excursion probability sensitivities with respect the thickness of the core shear walls

Challenge 2: Probability Sensitivity



Challenge 3: Optimal Design

- Failure probability
 - Number between 0 and 1, quantifies level of safety
 - **What is the use of this?**
- Reliability-based optimization (RBO)
 - Minimizing costs of construction, maintenance and eventual failure considering uncertainties

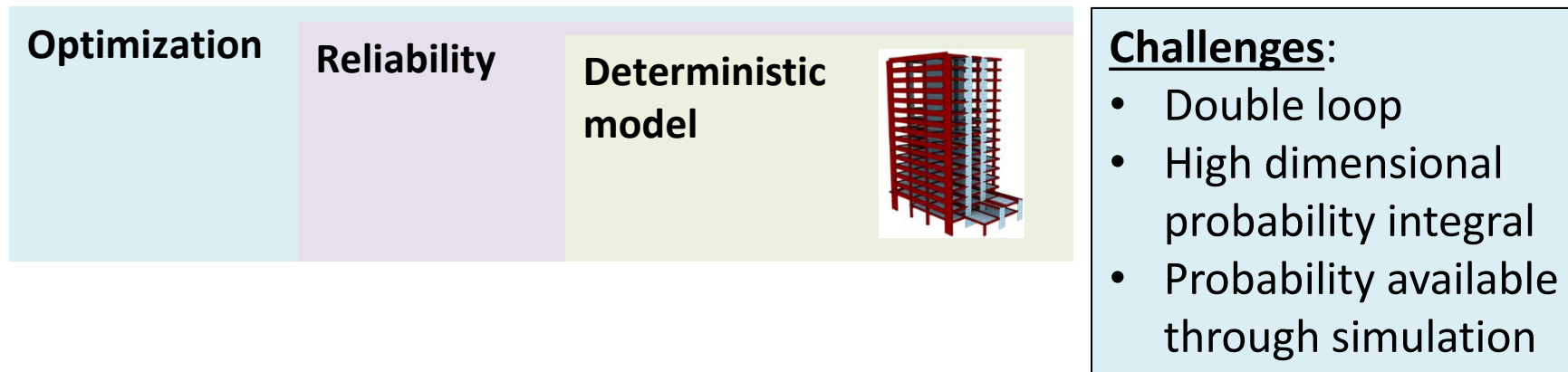


Challenge 3: Optimal Design

- Type of problem considered
 - Minimization of failure probability subject to budget constraint

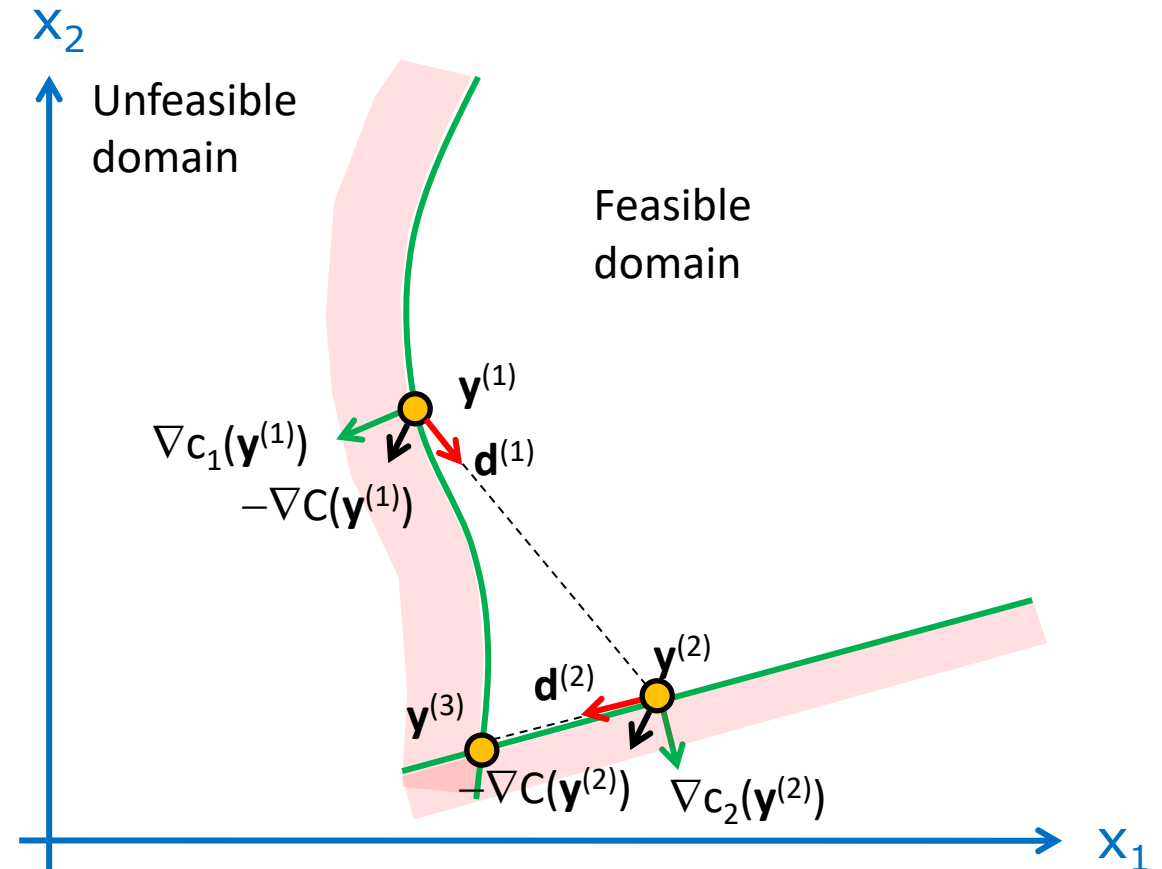
$$\begin{aligned} &\min_{\mathbf{y}} C(\mathbf{y}) \\ &\text{subject to} \\ &p_F(\mathbf{y}) \leq p_F^t \\ &c_l(\mathbf{y}) \leq 0, \quad l = 1, \dots, n_C \end{aligned}$$

- $C(\mathbf{y})$: cost function
- p_F^t : maximum allowable probability
- $c_l(\mathbf{y})$: deterministic constraints (e.g. geometry, bounds)



Challenge 3: Optimal Design

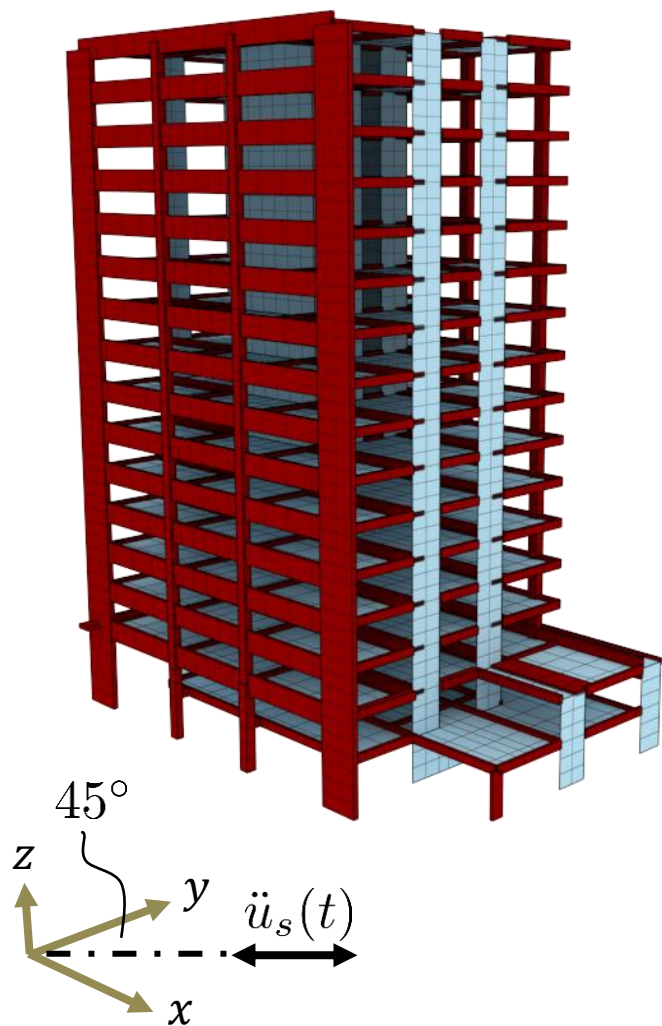
- RBO strategy
 - Gradient-based optimization
 - Feasible-direction interior point algorithm*
 - Line search performed with surrogate
 - Sequence of feasible, improved designs



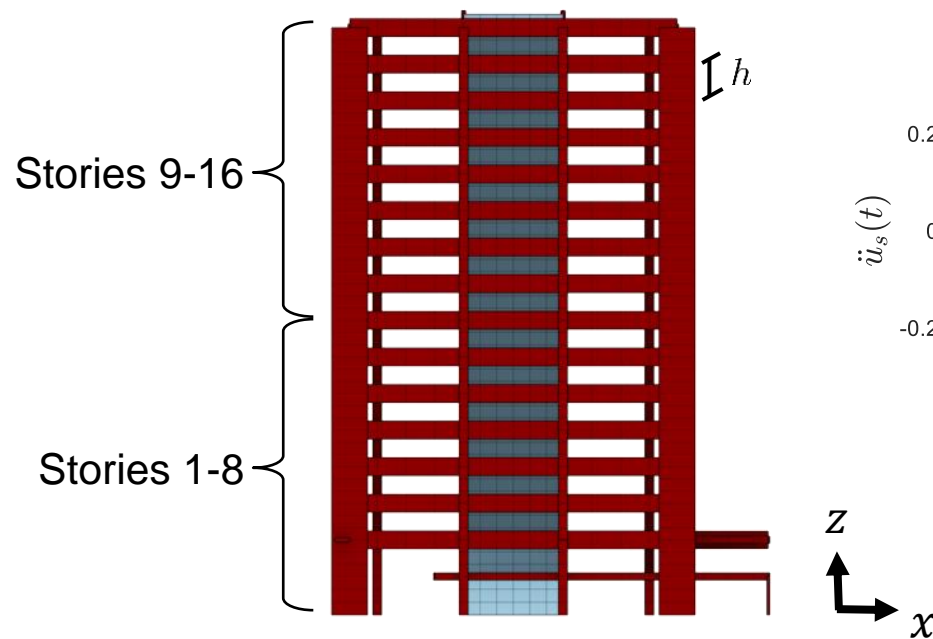
*J. Herskovits and G. Santos, "On the computer implementation of feasible direction interior point algorithms for nonlinear optimization," Structural Optimization, vol. 14, Art. no. 2–3, 1997.

Challenge 3: Optimal Design

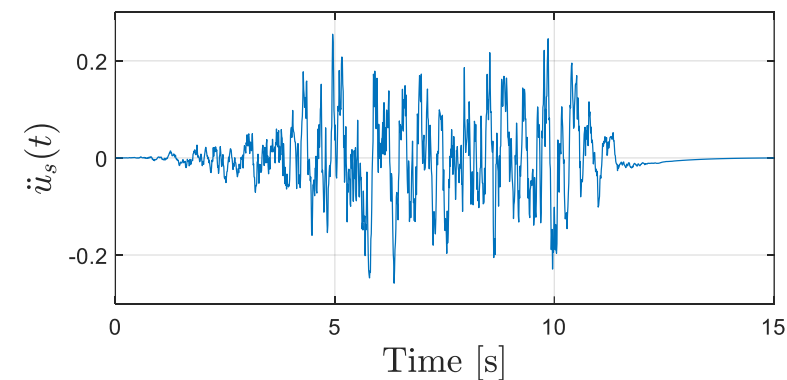
Perspective view



Elevation view



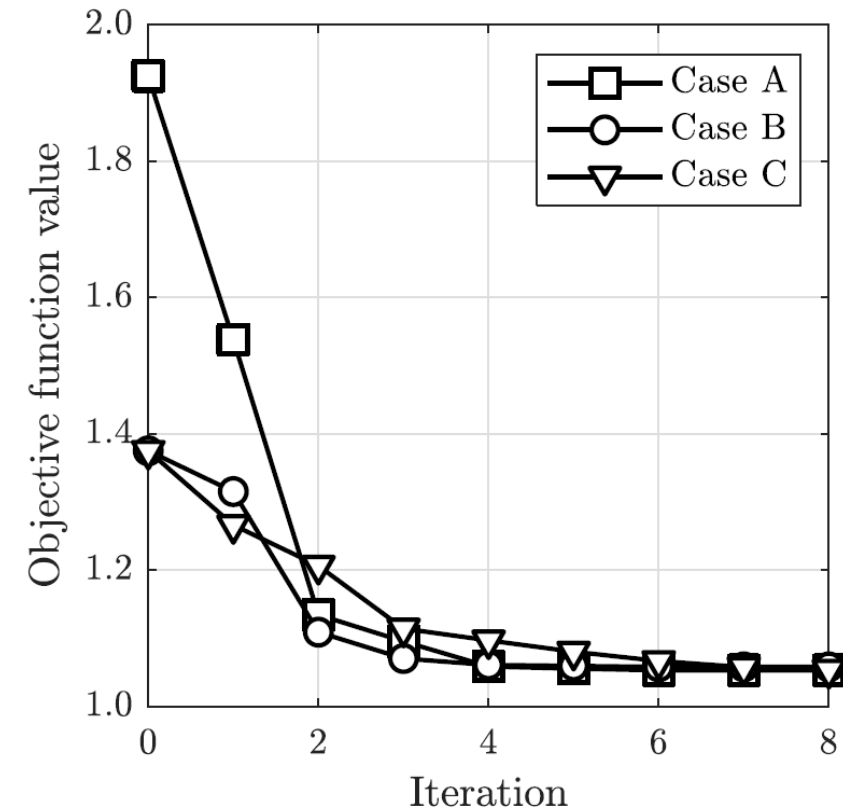
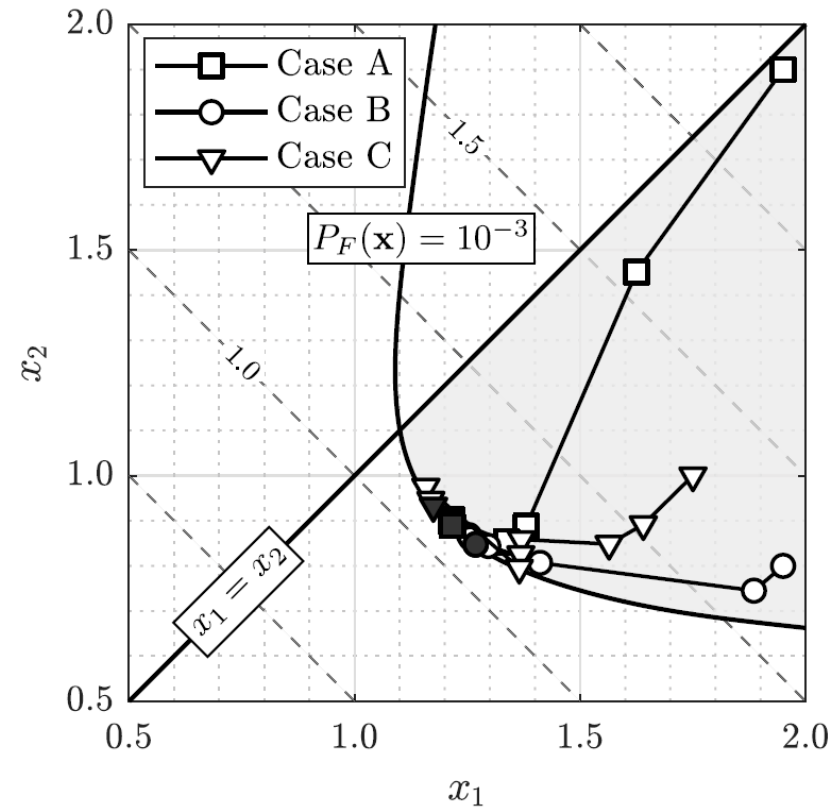
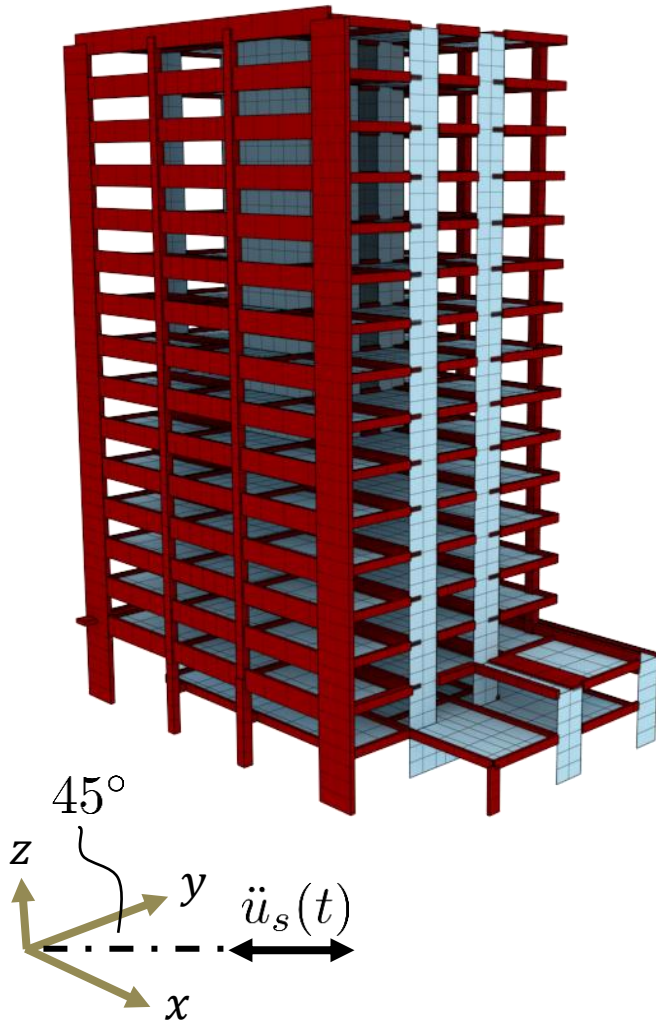
Realization of stochastic load



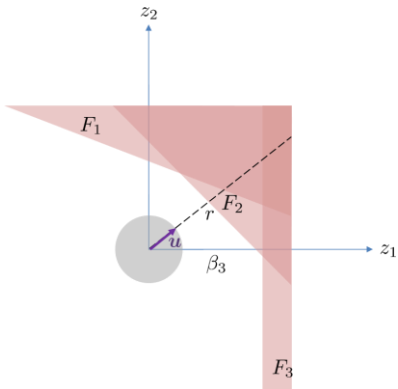
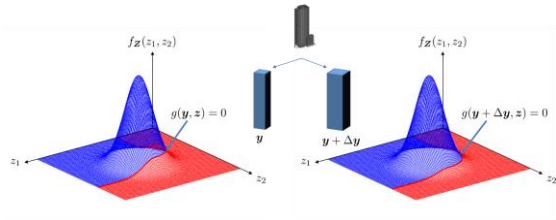
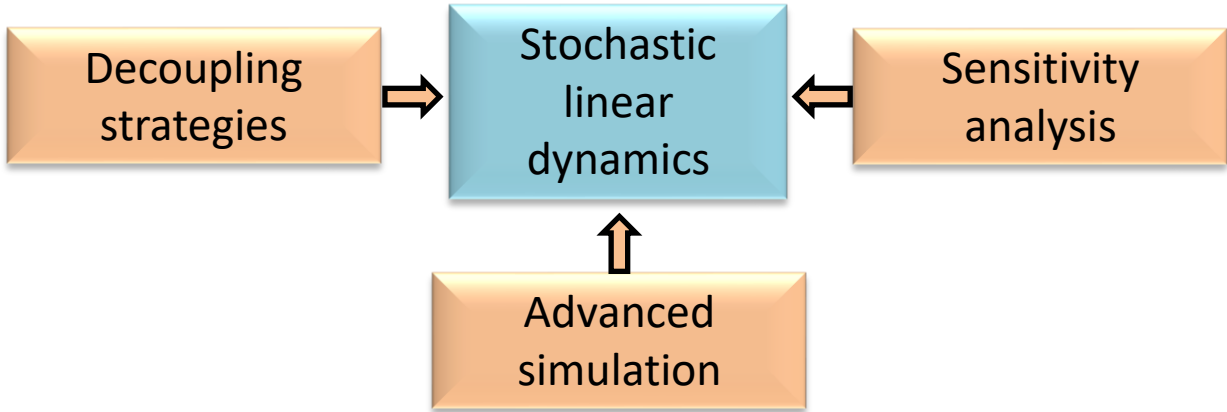
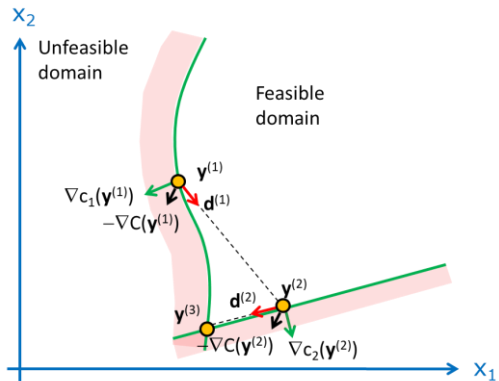
- Example: minimize thickness of walls (stories 1-8, 9-16) subject to probability of exceeding interstory drift threshold below 10^{-3}

Challenge 3: Optimal Design

Perspective view



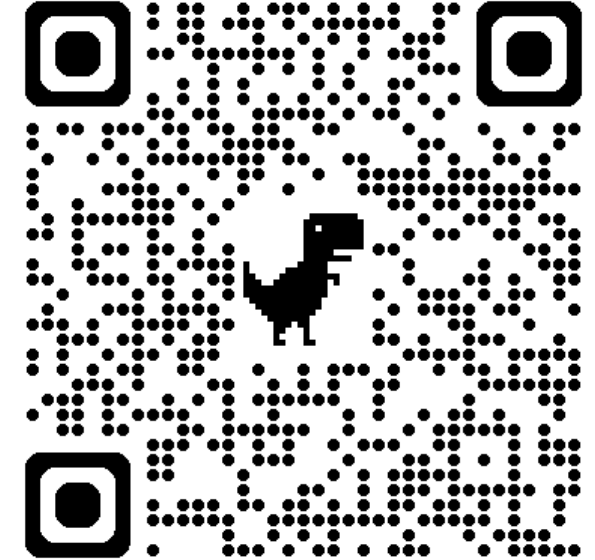
Conclusions



Open challenges: non-Gaussianity, non-linearity

References

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<https://www.researchgate.net/profile/Marcos-Valdebenito>

Simulation methods for analysis and design in stochastic linear dynamics

Marcos Valdebenito¹
¹TU Dortmund, Germany



Michael Beer



Matthias Faes



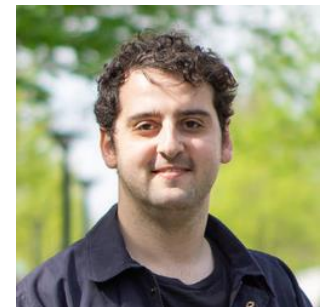
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