

10th World Congress on Structural and Multidisciplinary Optimization

**TOPOLOGY OPTIMIZATION OF STRUCTURES UNDER
STOCHASTIC EXCITATIONS**

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Orlando, Florida, May 21, 2013



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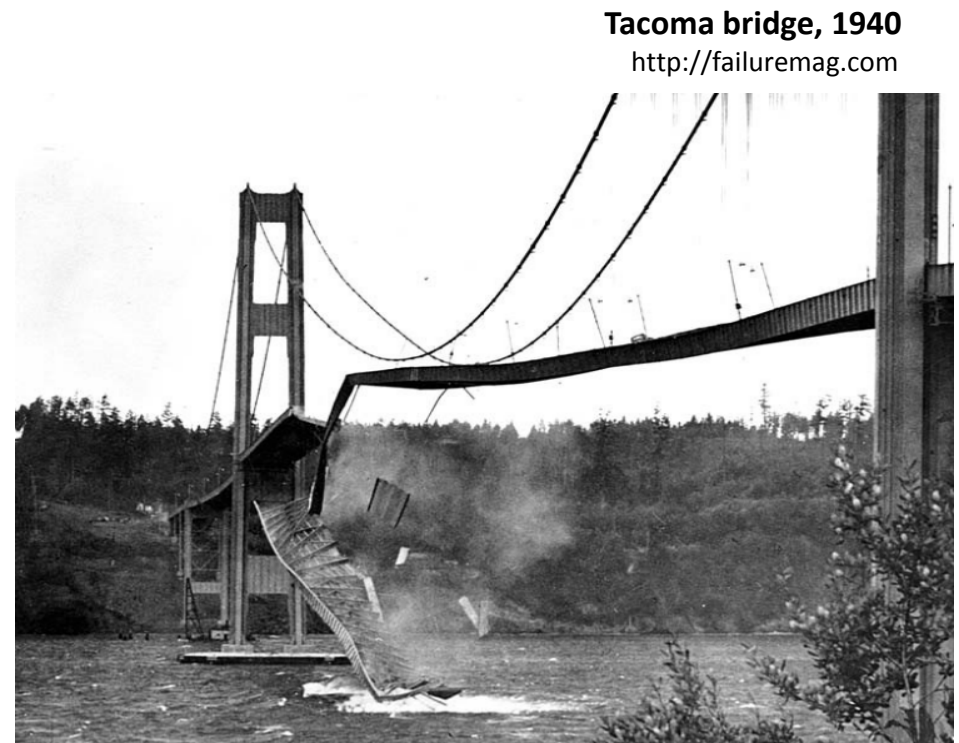


Structural engineering in Natural hazards and risks



San Francisco Earthquake, 1907

<http://www.documentingreality.com>



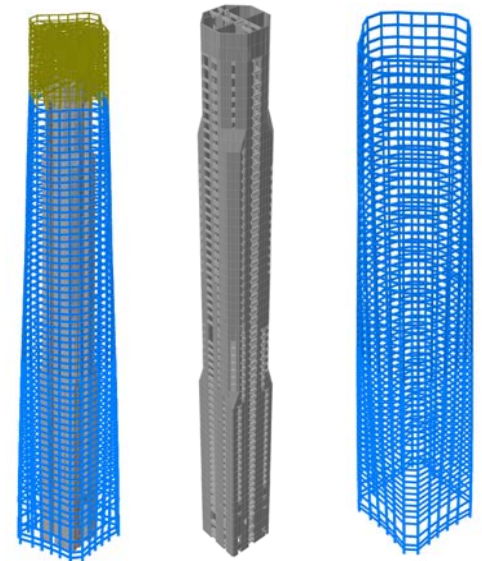
Tacoma bridge, 1940

<http://failuremag.com>

Structural engineering in Natural hazards and risks



Courtesy of Skidmore, Owing and Merrill, LLP



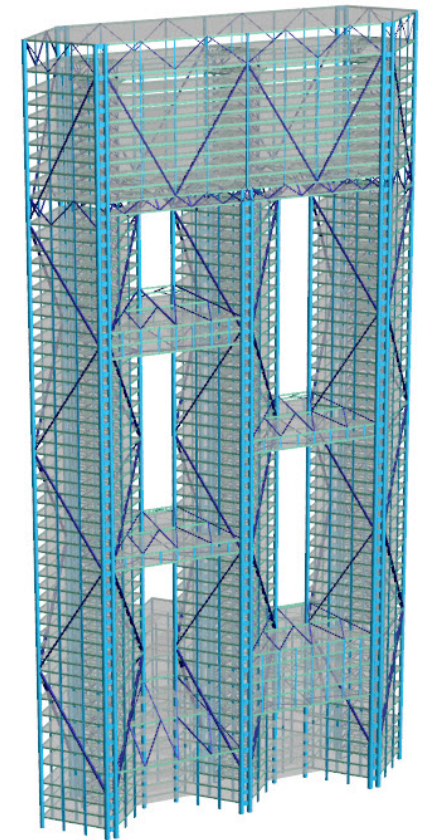
Motivation



John Hancock Center
http://en.wikipedia.org/wiki/John_Hancock_Center



Ssiger International Plaza
Courtesy of Skidmore, Owing and Merrill, LLP



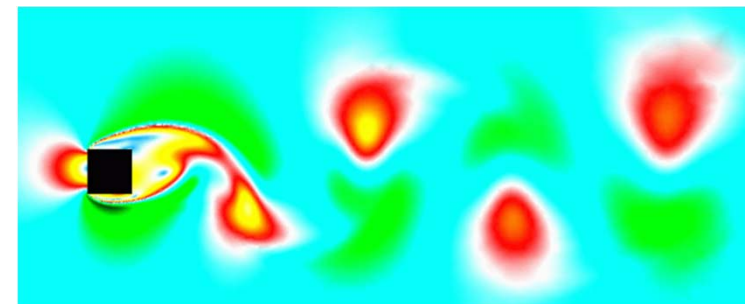
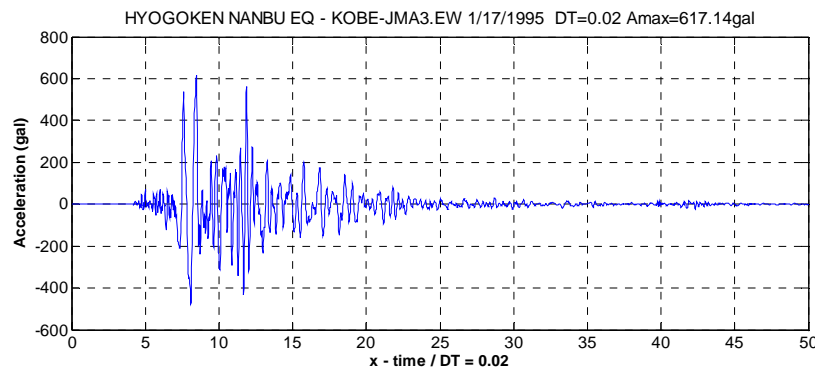
Motivation

- Topology optimization



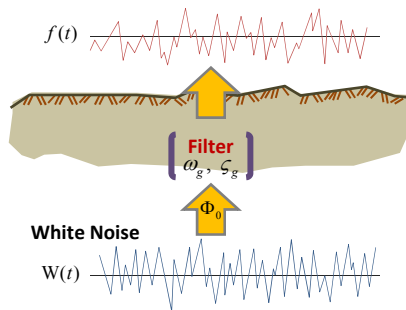
Stromberg, Beghini, Baker and Paulino (2011)

- Stochastic excitation

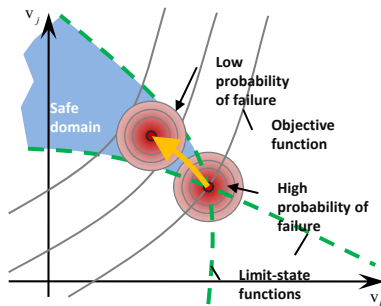


"Application of layout and topology optimization using pattern gradation for the conceptual design of buildings." L.L. Stromberg, A. Beghini, W. F. Baker, and G. H. Paulino. Structural and Multidisciplinary Optimization. Vol 43, No. 2, pp. 165-180, 2011.

1. Discrete representation method



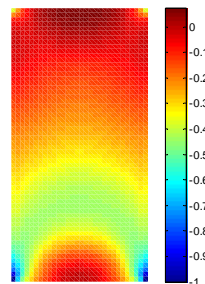
2. Instantaneous failure probability



3. Stochastic topology optimization

$$\begin{aligned} \min_{\mathbf{d}} \quad & f_{obj}(\tilde{\mathbf{p}}(\mathbf{d})) \\ \text{s.t.} \quad & P(E_f) \leq P_f^{\text{target}} \\ \text{with} \quad & \mathbf{M}(\tilde{\mathbf{p}})\ddot{\mathbf{u}}(t, \tilde{\mathbf{p}}) + \mathbf{C}(\tilde{\mathbf{p}})\dot{\mathbf{u}}(t, \tilde{\mathbf{p}}) + \mathbf{K}(\tilde{\mathbf{p}})\mathbf{u}(t, \tilde{\mathbf{p}}) = \mathbf{f}(t, \tilde{\mathbf{p}}) \end{aligned}$$

4. Sensitivity



5. Numerical examples



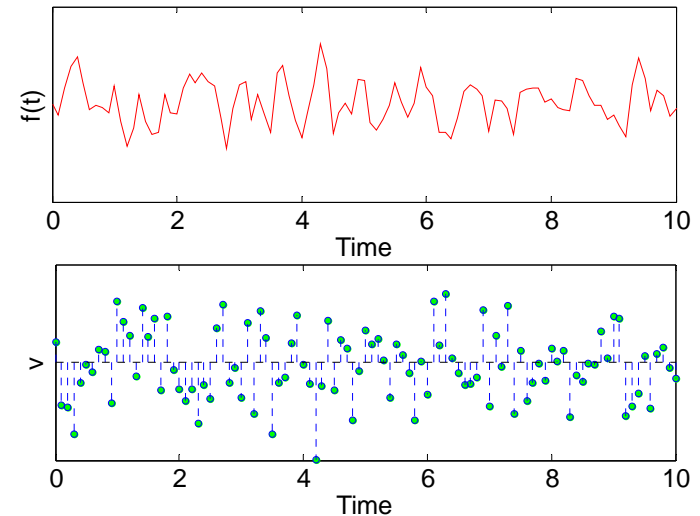
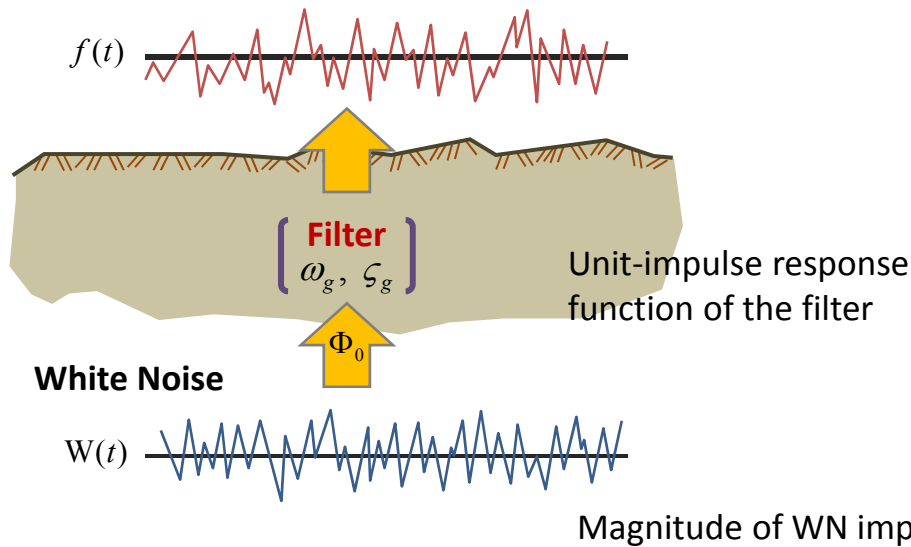
Discrete representation method

- General (random process)

$$f(t) = \mu(t) + \sum_{i=1}^n v_i s_i(t) = \mu(t) + \mathbf{s}(t)^T \mathbf{v}$$

- v : uncorrelated standard normal random variables
- $s(t)$: deterministic basis functions based on the spectral characteristics of the process

- Example : Filtered white noise (earthquake)



$$\begin{aligned}
 f(t) &= \int_0^t v(\tau) s(t-\tau) d\tau \\
 &\cong \sum_{i=1}^n v_i s_i(t) = \sum_{i=1}^n W_i \cdot h_f(t-t_i) \Delta t \\
 &= \sum_{i=1}^n \sqrt{2\pi\Phi_0 / \Delta t} \cdot v_i \cdot h_f(t-t_i) \Delta t = \mathbf{s}(t)^T \mathbf{v}
 \end{aligned}$$

Response of Linear System to Stochastic Excitation

Linear system + Gaussian

- Duhamel's Integral

$$u(t) = \int_0^t f(\tau)h_s(t-\tau)d\tau$$

- $h_s(t)$: the unit-impulse response function of the system

- Response

$$u(t) = \int_0^t \sum_{i=1}^n v_i s_i(\tau) h_s(t-\tau) d\tau = \sum_{i=1}^n v_i a_i(t) = \mathbf{a}(t)^T \mathbf{v}$$

$$a_i(t) = \int_0^t s_i(\tau) h_s(t-\tau) d\tau, \quad i = 1, \dots, n$$

Deterministic, time-dependent
 - filter + structure

Random, time-independent

- MDOF in FEM settings

$$\begin{pmatrix} u(t_1) \\ u(t_2) \\ \vdots \\ u(t_{n-1}) \\ u(t_n) \end{pmatrix} = \begin{pmatrix} u(\Delta t) \\ u(2\Delta t) \\ \vdots \\ u(t_0 - \Delta t) \\ u(t_0) \end{pmatrix} = \begin{bmatrix} 0 & 0 & \cdots & 0 & v_1 \\ 0 & 0 & \cdots & v_1 & v_2 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & v_1 & \cdots & v_{n-2} & v_{n-1} \\ v_1 & v_2 & \cdots & v_{n-1} & v_n \end{bmatrix} \begin{pmatrix} a_1(t_0) \\ a_2(t_0) \\ \vdots \\ a_{n-1}(t_0) \\ a_n(t_0) \end{pmatrix}$$

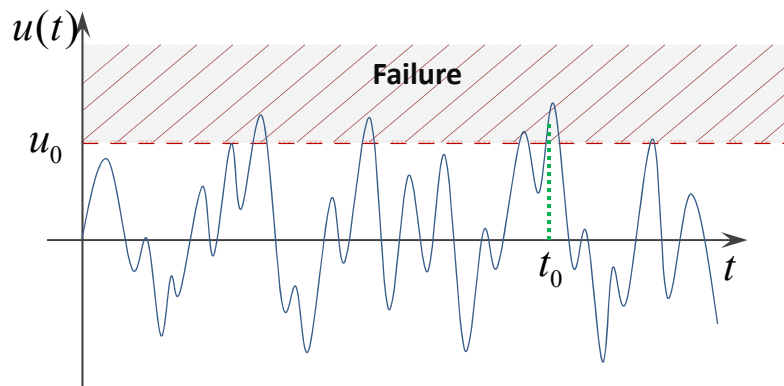
Numerical time integration

Inversely computed

Instantaneous failure probability

- ‘Instantaneous’ failure events of a linear system

$$E_f = \{u(t_0) \geq u_0\} = \{\mathbf{a}(t_0)^T \mathbf{v} \geq u_0\}$$



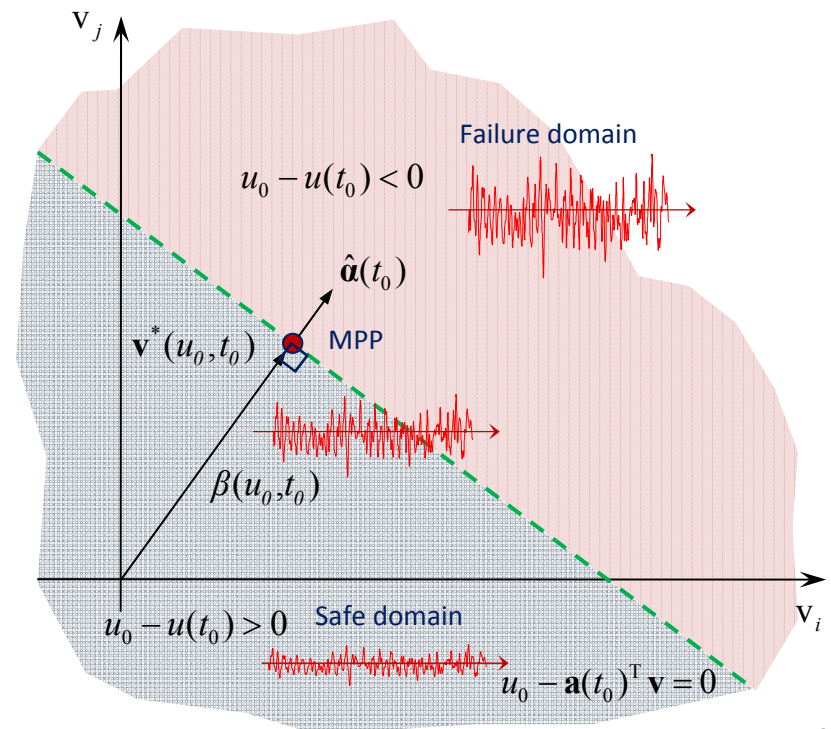
- Failure Probability, $P(E_f)$

$$P(u(t_0) \geq u_0) = P(u_0 - \mathbf{a}^T(t_0) \mathbf{v} \leq 0) = P(g(u) \leq 0)$$

$$g(u) = \frac{u_0}{\|\mathbf{a}(t_0)\|} - \frac{\mathbf{a}^T(t_0)}{\|\mathbf{a}(t_0)\|} \mathbf{v} = \beta(u_0, t_0) - \hat{\mathbf{a}}(t_0) \cdot \mathbf{v}$$

$$P(u(t_0) \geq u_0) = \Phi[-\beta(u_0, t_0)]$$

$$\beta(u_0, t_0) = u_0 / \|\mathbf{a}(t_0)\| = \hat{\mathbf{a}}(t_0) \cdot \mathbf{v}^*$$



Stochastic topology optimization formulation

$$\begin{aligned} & \min_{\mathbf{d}} f_{obj}(\tilde{\rho}(\mathbf{d})) \\ & s.t. \quad P(E_f) \leq P_f^{target} \\ & with \quad \mathbf{M}(\tilde{\rho})\ddot{\mathbf{u}}(t, \tilde{\rho}) + \mathbf{C}(\tilde{\rho})\dot{\mathbf{u}}(t, \tilde{\rho}) + \mathbf{K}(\tilde{\rho})\mathbf{u}(t, \tilde{\rho}) = \mathbf{f}(t, \tilde{\rho}) \end{aligned}$$

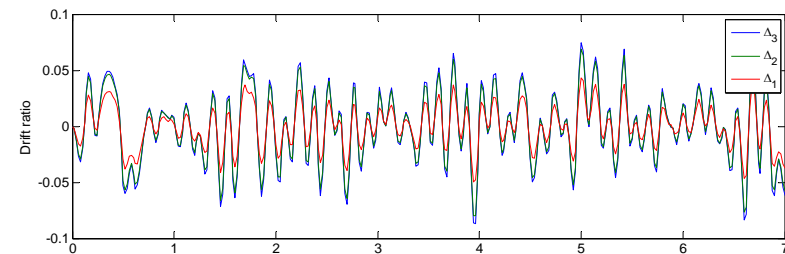
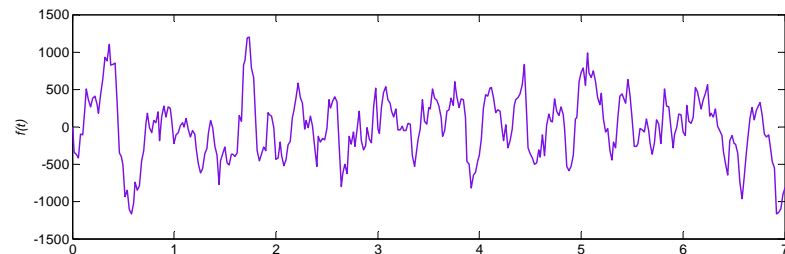
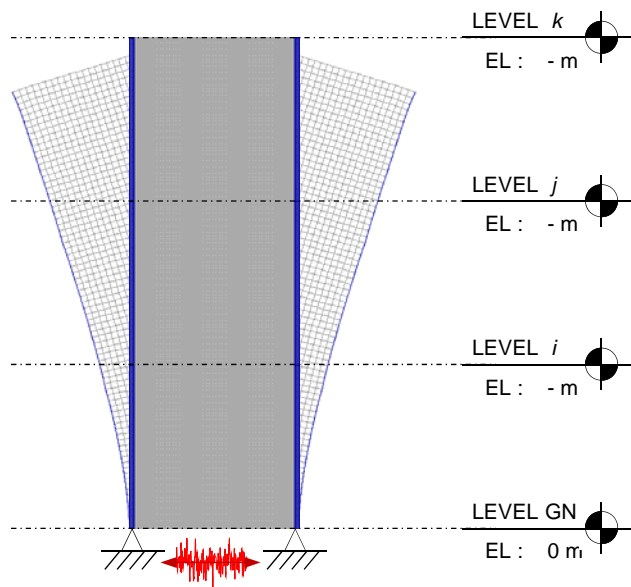
How to compute sensitivity in an efficient way

$\tilde{\rho}$: Filtered density

M: Mass matrix, **C**: Damping matrix, **K**: Stiffness matrix

$f(t)$: Stochastic process (e.g., for earthquake loading $\mathbf{f}(t) = -\mathbf{M}\ddot{\mathbf{u}}_g(t) = -\mathbf{M}\mathbf{f}(t)$)

E_f : Failure event, P_f^{target} : Target failure probability



Sensitivity calculation

Computing the sensitivity of structural responses with respect to various design parameters is essential for efficient gradient-based optimization

- Probabilistic constraint on of an instantaneous failure event

$$P(E_f) = P(u_0 - \mathbf{a}(t_0, \tilde{\boldsymbol{\rho}})^T \mathbf{v} \leq 0) \leq P_f^{\text{target}}$$

- Alternatively,

$$\Phi[-\beta(u_0, t_0, \tilde{\boldsymbol{\rho}})] \leq \Phi(-\beta^{\text{target}})$$

- Sensitivity of the reliability index with respect to the design variable is derived as

$$\begin{aligned} \frac{\partial \beta(u_0, t_0, \tilde{\boldsymbol{\rho}})}{\partial d_e} &= \sum_{j=1}^{n_e} \frac{\partial \beta(u_0, t_0, \tilde{\boldsymbol{\rho}})}{\partial \tilde{\rho}_j} \cdot \frac{\partial \tilde{\rho}_j}{\partial d_e} & \beta(u_0, t_0) &= \frac{u_0}{\|\mathbf{a}(t_0)\|} \\ &= \left[-\frac{u_0}{(a_1(t_0, \tilde{\boldsymbol{\rho}})^2 + \dots + a_n(t_0, \tilde{\boldsymbol{\rho}})^2)^{\frac{3}{2}}} \right] \cdot \sum_{j=1}^{n_e} \sum_{i=1}^n \left(a_i(t_0, \tilde{\boldsymbol{\rho}}) \cdot \frac{\partial a_i(t_0, \tilde{\boldsymbol{\rho}})}{\partial \tilde{\rho}_j} \right) \cdot \frac{\partial \tilde{\rho}_j}{\partial d_e} \\ &= \sum_{j=1}^{n_e} \sum_{i=1}^n \left(c_i(u_0, t_0, \tilde{\boldsymbol{\rho}}) \cdot \frac{\partial a_i(t_0, \tilde{\boldsymbol{\rho}})}{\partial \tilde{\rho}_j} \right) \frac{\partial \tilde{\rho}_j}{\partial d_e} \end{aligned}$$

Implicitly defined term

Sensitivity calculation-cont'd

- Adjoint method by introducing adjoint system equation (Newmark method)

$$\begin{aligned} & \left(\frac{1}{\eta(\Delta t)^2} \mathbf{M}(\tilde{\rho}) + \frac{\gamma}{\eta\Delta t} \mathbf{C}(\tilde{\rho}) + \mathbf{K}(\tilde{\rho}) \right) \mathbf{u}(t_{j+1}, \tilde{\rho}) = \mathbf{f}(t_{j+1}, \tilde{\rho}) \\ & + \mathbf{C}(\tilde{\rho}) \left[\frac{\gamma}{\eta\Delta t} \mathbf{u}(t_j, \tilde{\rho}) + \left(\frac{\gamma}{\eta} - 1 \right) \dot{\mathbf{u}}(t_j, \tilde{\rho}) + \Delta t \left(\frac{\gamma}{2\eta} - 1 \right) \ddot{\mathbf{u}}(t_j, \tilde{\rho}) \right] \\ & + \mathbf{M}(\tilde{\rho}) \left[\frac{1}{\eta(\Delta t)^2} \mathbf{u}(t_j, \tilde{\rho}) + \frac{1}{\eta\Delta t} \dot{\mathbf{u}}(t_j, \tilde{\rho}) + \left(\frac{1}{2\eta} - 1 \right) \ddot{\mathbf{u}}(t_j, \tilde{\rho}) \right] \end{aligned}$$

- From a general recurrence relation associated with three sequential displacements (Chan et al. 1962, Zienkiewicz 1977)

$$\begin{aligned} & \left(\mathbf{M}(\tilde{\rho}) + \gamma\Delta t\mathbf{C}(\tilde{\rho}) + \eta(\Delta t)^2 \mathbf{K}(\tilde{\rho}) \right) \mathbf{u}(t_{j+1}, \tilde{\rho}) = \eta(\Delta t)^2 \mathbf{f}(t_{j+1}, \tilde{\rho}) + (0.5 + \gamma - 2\eta)(\Delta t)^2 \mathbf{f}(t_j, \tilde{\rho}) \\ & + (0.5 - \gamma + \eta)(\Delta t)^2 \mathbf{f}(t_{j-1}, \tilde{\rho}) \\ & - \left[-2\mathbf{M}(\tilde{\rho}) + (1 - 2\gamma)\Delta t\mathbf{C}(\tilde{\rho}) + (0.5 + \gamma - 2\eta)(\Delta t)^2 \mathbf{K}(\tilde{\rho}) \right] \mathbf{u}(t_j, \tilde{\rho}) \\ & - \left[\mathbf{M}(\tilde{\rho}) + (\gamma - 1)\Delta t\mathbf{C}(\tilde{\rho}) + (0.5 - \gamma + \eta)(\Delta t)^2 \mathbf{K}(\tilde{\rho}) \right] \mathbf{u}(t_{j-1}, \tilde{\rho}) \end{aligned}$$

Sensitivity calculation-cont'd

- By pre-multiplying the discretized adjoint system with the dimensional adjoint variable vector and adding to right-hand side terms of the original sensitivity equation

$$\begin{aligned} \frac{\partial \beta(u_0, t_0, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} &= \sum_{i=1}^n \left(T_i \cdot \mathbf{z}^T \frac{\partial \mathbf{u}(t_i, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \right) \\ &+ \sum_{j=1}^n \lambda_{n-j+1}^T \left[\frac{\partial \underline{\mathbf{A}}(\tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \cdot \mathbf{u}(t_j, \tilde{\mathbf{p}}) - \eta (\Delta t)^2 \frac{\partial \mathbf{f}(t_j, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} - (0.5 + \gamma - 2\eta) (\Delta t)^2 \frac{\partial \mathbf{f}(t_{j-1}, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \right. \\ &\left. - (0.5 - \gamma + \eta) (\Delta t)^2 \frac{\partial \mathbf{f}(t_{j-2}, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} + \frac{\partial \underline{\mathbf{B}}(\tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \cdot \mathbf{u}(t_{j-1}, \tilde{\mathbf{p}}) + \frac{\partial \underline{\mathbf{E}}(\tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \cdot \mathbf{u}(t_{j-2}, \tilde{\mathbf{p}}) \right] \\ &+ \sum_{j=1}^n \lambda_{n-j+1}^T \left[\underline{\mathbf{A}}(\tilde{\mathbf{p}}) \cdot \frac{\partial \mathbf{u}(t_j, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} + \underline{\mathbf{B}}(\tilde{\mathbf{p}}) \cdot \frac{\partial \mathbf{u}(t_{j-1}, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} + \underline{\mathbf{E}}(\tilde{\mathbf{p}}) \cdot \frac{\partial \mathbf{u}(t_{j-2}, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \right] \end{aligned}$$

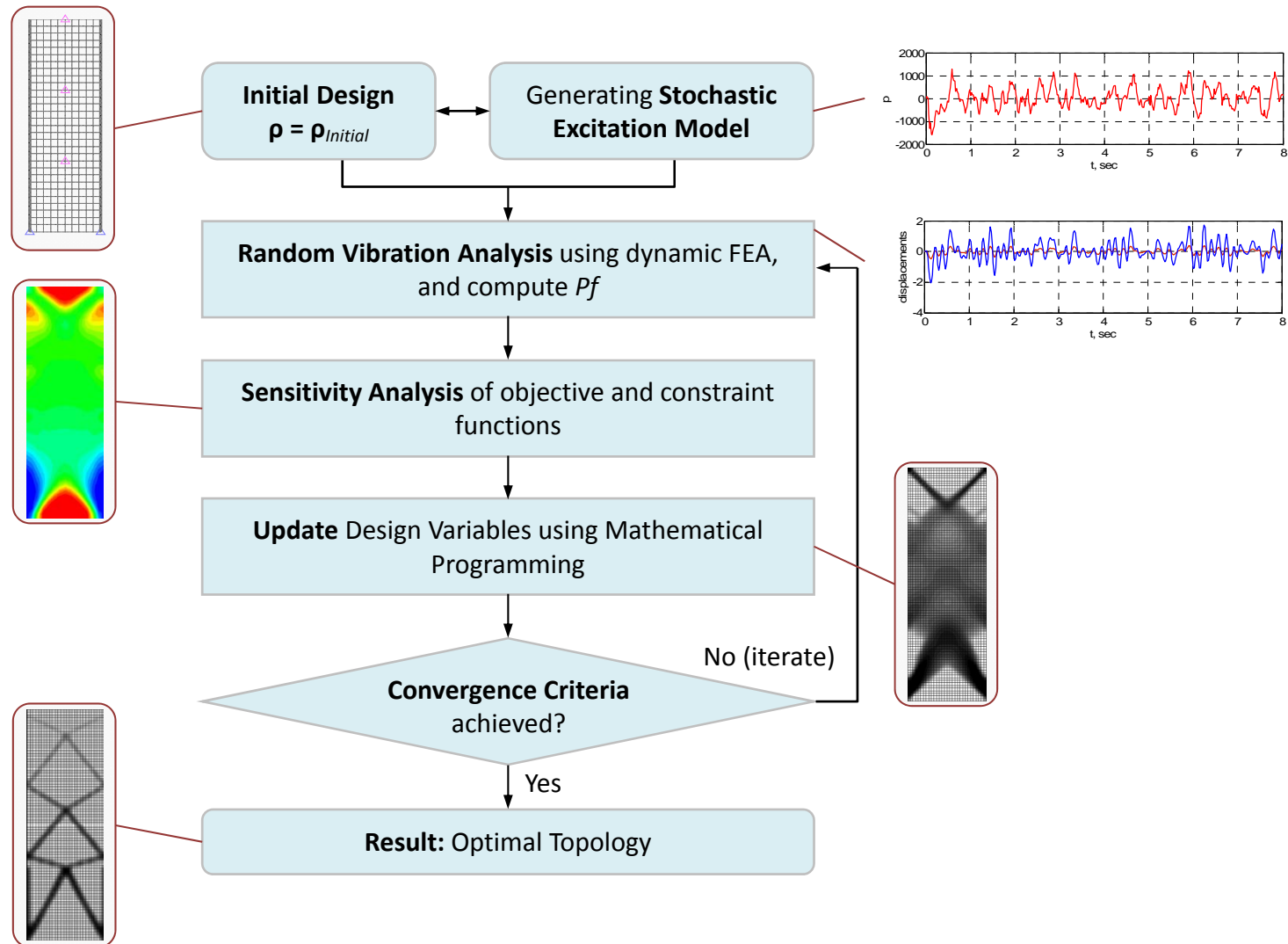
$$\sum_{i=1}^n \left(c_i(t_0, \tilde{\mathbf{p}}) \cdot \frac{\partial a_i(t_0, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \right) = \sum_{i=1}^n \left(T_i \cdot \mathbf{z}^T \cdot \frac{\partial \mathbf{u}(t_i, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \right)$$

$$\begin{aligned} \underline{\mathbf{A}}(\tilde{\mathbf{p}}) &= \mathbf{M}(\tilde{\mathbf{p}}) + \gamma \Delta t \cdot \mathbf{C}(\tilde{\mathbf{p}}) + \eta (\Delta t)^2 \mathbf{K}(\tilde{\mathbf{p}}) \\ \underline{\mathbf{B}}(\tilde{\mathbf{p}}) &= -2\mathbf{M}(\tilde{\mathbf{p}}) + (1 - 2\gamma) \Delta t \mathbf{C}(\tilde{\mathbf{p}}) + (0.5 + \gamma - 2\eta) (\Delta t)^2 \mathbf{K}(\tilde{\mathbf{p}}) \\ \underline{\mathbf{E}}(\tilde{\mathbf{p}}) &= \mathbf{M}(\tilde{\mathbf{p}}) + (\gamma - 1) \Delta t \mathbf{C}(\tilde{\mathbf{p}}) + (0.5 - \gamma + \eta) (\Delta t)^2 \mathbf{K}(\tilde{\mathbf{p}}) \end{aligned}$$

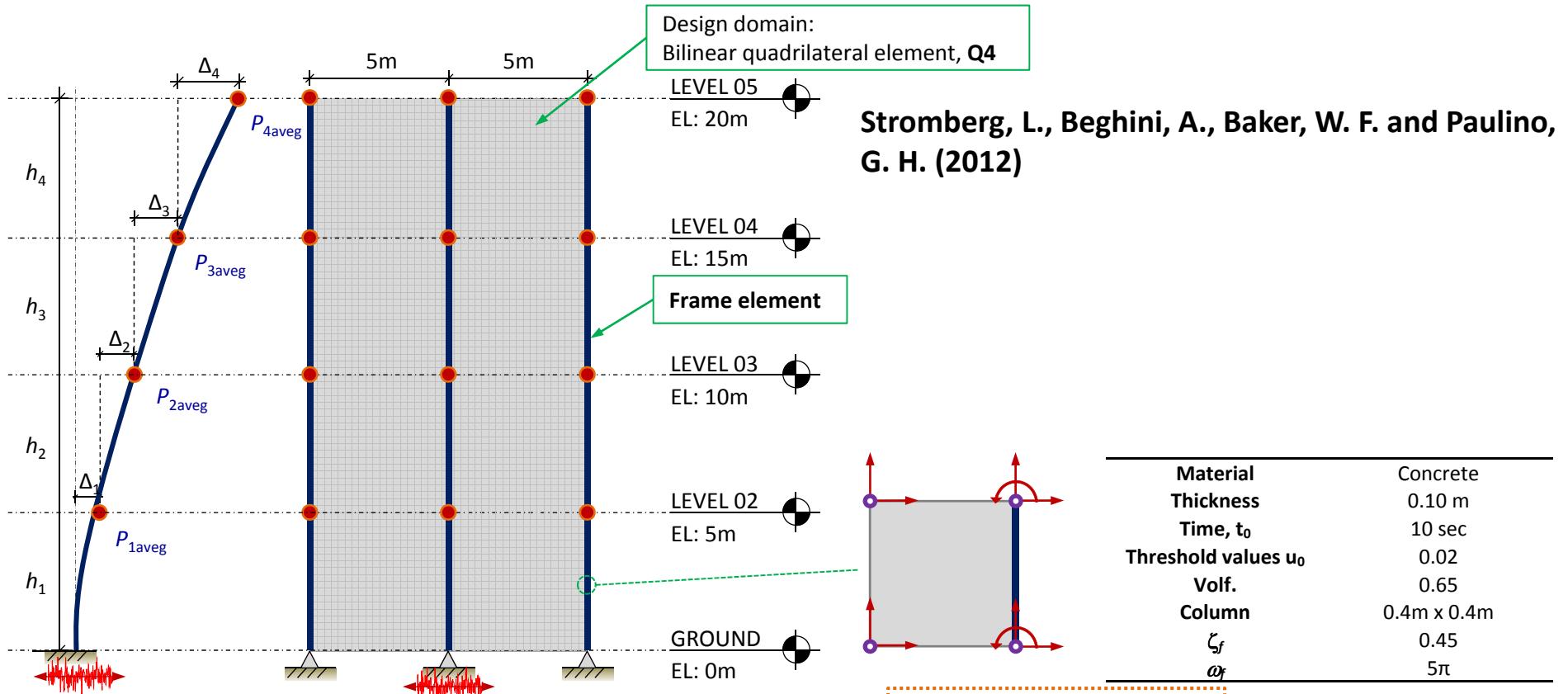
- After solving adjoint system problem

$$\begin{aligned} \frac{\partial \beta(u_0, t_0, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} &= \sum_{j=1}^n \lambda_{n-j+1}^T \left[\frac{\partial \underline{\mathbf{A}}(\tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \cdot \mathbf{u}(t_j, \tilde{\mathbf{p}}) - \eta (\Delta t)^2 \frac{\partial \mathbf{f}(t_j, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} - (0.5 + \gamma - 2\eta) (\Delta t)^2 \frac{\partial \mathbf{f}(t_{j-1}, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \right. \\ &\left. - (0.5 - \gamma + \eta) (\Delta t)^2 \frac{\partial \mathbf{f}(t_{j-2}, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} + \frac{\partial \underline{\mathbf{B}}(\tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \cdot \mathbf{u}_{j-1}(\tilde{\mathbf{p}}) + \frac{\partial \underline{\mathbf{E}}(\tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \cdot \mathbf{u}(t_{j-2}, \tilde{\mathbf{p}}) \right] \\ &+ \lambda_n^T \left[\underline{\mathbf{B}}(\tilde{\mathbf{p}}) \cdot \frac{\partial \mathbf{u}(0, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} + \underline{\mathbf{E}}(\tilde{\mathbf{p}}) \cdot \frac{\partial \mathbf{u}(t_{-1}, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \right] + \lambda_{n-1}^T \left[\underline{\mathbf{E}}(\tilde{\mathbf{p}}) \cdot \frac{\partial \mathbf{u}(0, \tilde{\mathbf{p}})}{\partial \tilde{\rho}_j} \right] \end{aligned}$$

Flow chart for topology optimization under stochastic excitations



Numerical example : Building structure



Stromberg, L., Beghini, A., Baker, W. F. and Paulino, G. H. (2012)

$$\min_{\mathbf{d}} V(\tilde{\mathbf{p}}(\mathbf{d}))$$

$$s.t. P(E_f) \leq P_f^{\text{target}}$$

$$\text{with } \mathbf{M}(\tilde{\mathbf{p}})\ddot{\mathbf{u}}(t, \tilde{\mathbf{p}}) + \mathbf{C}(\tilde{\mathbf{p}})\dot{\mathbf{u}}(t, \tilde{\mathbf{p}}) + \mathbf{K}(\tilde{\mathbf{p}})\mathbf{u}(t, \tilde{\mathbf{p}}) = -\mathbf{M}\mathbf{f}(t)$$

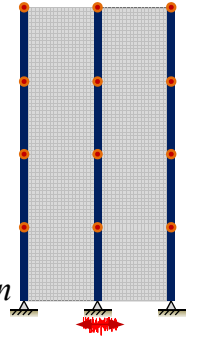
Inter-story drift ratio

Filtered Gaussian process using Kanai-Tajimi filter

Failure event - Inter-story drift ratio

$$E_{f_i} = \left\{ u_{i0} - \left(\frac{(\mathbf{a}(t_0, \tilde{\mathbf{p}})_{i,L}^T + \mathbf{a}(t_0, \tilde{\mathbf{p}})_{i,M}^T + \mathbf{a}(t_0, \tilde{\mathbf{p}})_{i,R}^T) \mathbf{v}}{nL_i} \right) \leq 0 \right\} \text{ for } i = 2$$

$$\left\{ u_{i0} - \left(\frac{(\mathbf{a}(t_0, \tilde{\mathbf{p}})_{i,L}^T + \mathbf{a}(t_0, \tilde{\mathbf{p}})_{i,M}^T + \mathbf{a}(t_0, \tilde{\mathbf{p}})_{i,R}^T) \mathbf{v}}{nL_i} - \frac{(\mathbf{a}(t_0, \tilde{\mathbf{p}})_{(i-1),L}^T + \mathbf{a}(t_0, \tilde{\mathbf{p}})_{(i-1),M}^T + \mathbf{a}(t_0, \tilde{\mathbf{p}})_{(i-1),R}^T) \mathbf{v}}{nL_i} \right) \leq 0 \right\} \text{ for } i = 3, 4, \dots, n$$



Filtered Gaussian process using KT filter

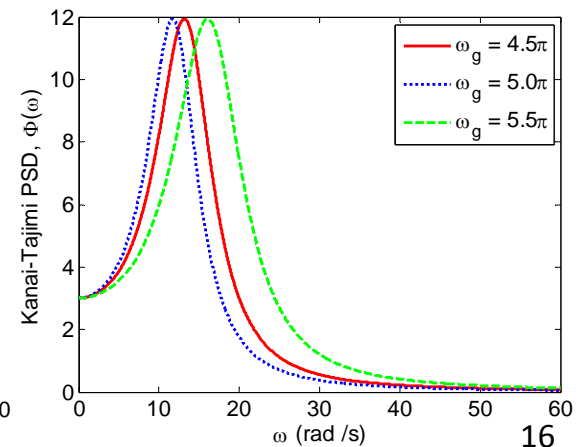
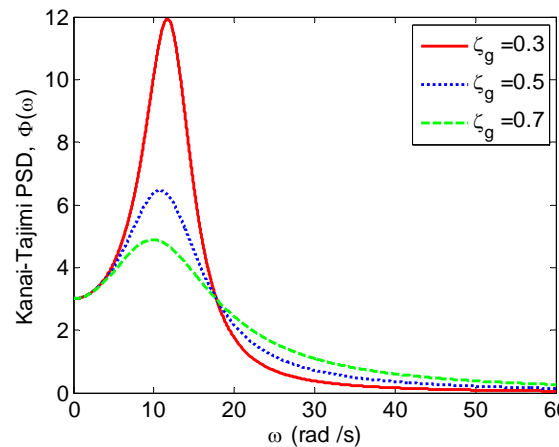
- Kanai-Tajimi filter model

$$h_f(t) = \exp(-\zeta_f \omega_f t) \left[\frac{(2\zeta_f^2 - 1)\omega_f}{\sqrt{1 - \zeta_f^2}} \sin(\omega_f \sqrt{1 - \zeta_f^2} \cdot t) - 2\zeta_f \omega_f \cos(\omega_f \sqrt{1 - \zeta_f^2} \cdot t) \right]$$

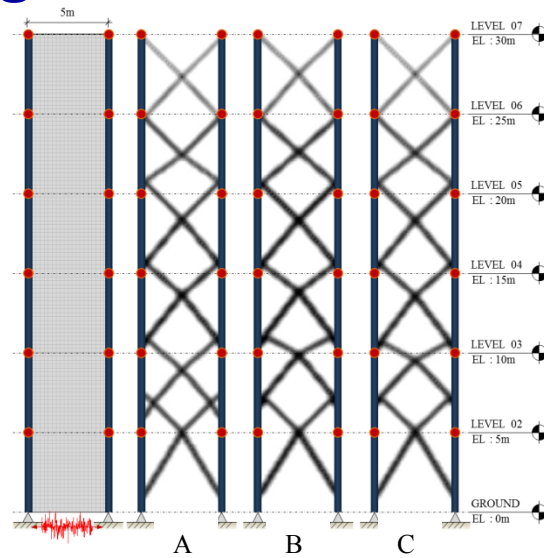
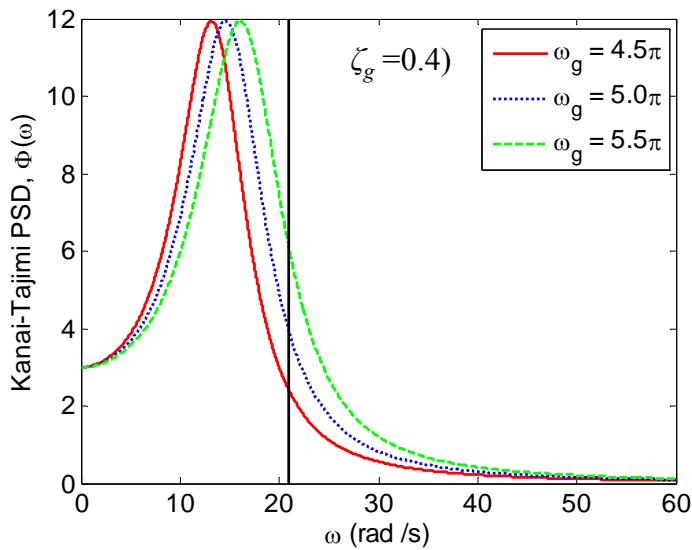
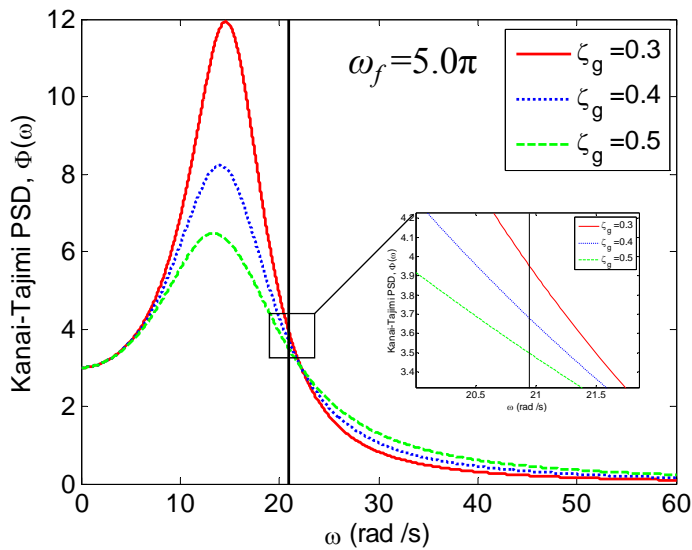
ζ_f : damping ratio of the filter
 ω_f : predominant frequency of the filter

$$\Phi(\omega) = \frac{1 + 4\zeta_f^2 (\omega / \omega_g)^2}{[1 - (\omega / \omega_g)^2]^2 + (2\zeta_f \omega / \omega_g)^2} \Phi_0$$

$$f(t) = \sum_{i=1}^n \sqrt{2\pi\Phi_0 / \Delta t} \cdot v_i \cdot h_f(t - t_i) \Delta t$$

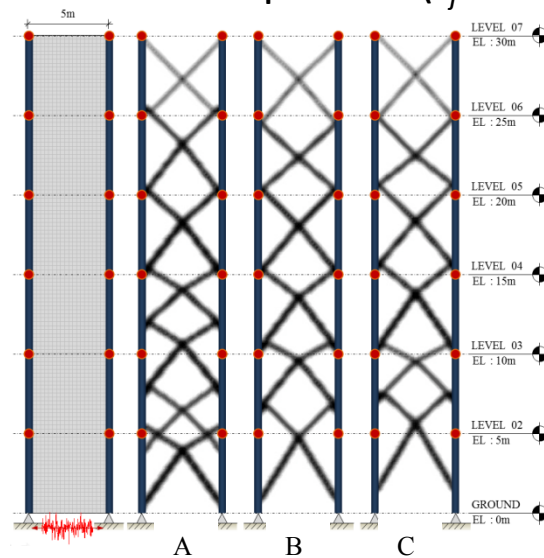


Parametric study on impact of ground motion characteristics



$\beta_{target}=1.5 = (P_f=6.68\%)$

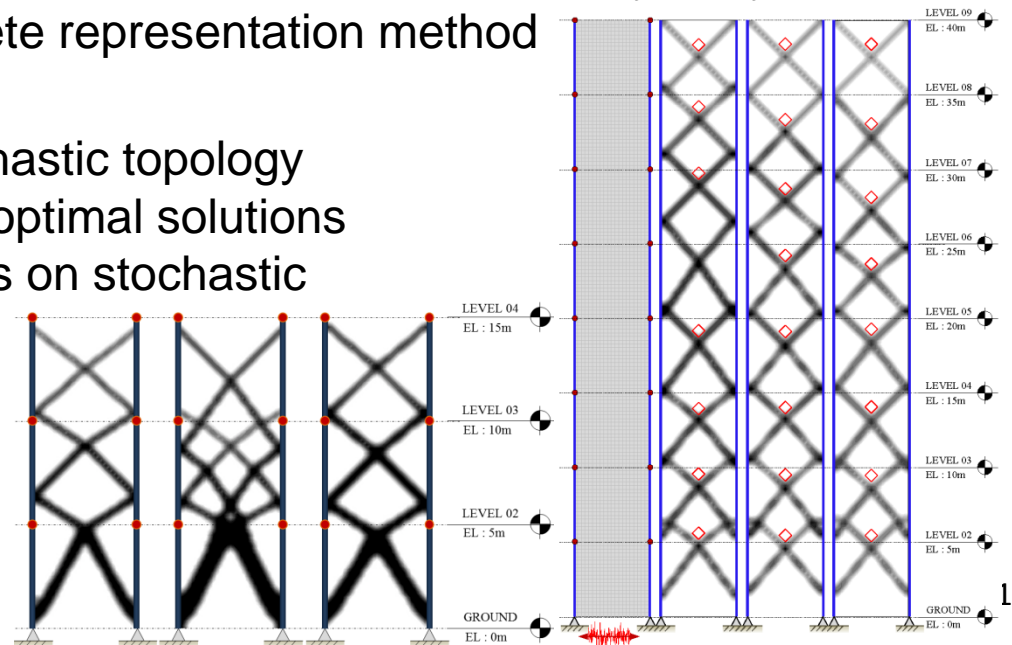
A ($\Phi_0=3, \beta_{target}=1.5$)	
ζ_f	0.3
Volume	2.81 m ³ (18.7%)
B ($\Phi_0=3, \beta_{target}=1.5$)	
ζ_f	0.4
Volume	2.42 m ³ (16.1%)
C ($\Phi_0=3, \beta_{target}=1.5$)	
ζ_f	0.5
Volume	2.27 m ³ (15.1%)



A ($\Phi_0=3, \beta_{target}=1.5$)	
ω_f	4.5 π
Volume	2.08 m ³ (13.9%)
B ($\Phi_0=3, \beta_{target}=1.5$)	
ω_f	5.0 π
Volume	2.42 m ³ (16.1%)
C ($\Phi_0=3, \beta_{target}=1.5$)	
ω_f	5.5 π
Volume	2.82 m ³ (18.8%)

Conclusions

- Introduction of a new approach incorporating random vibration theories into topology optimization using a discrete representation method for stochastic processes
- Computation of the failure probability regarding stochastic responses by a closed-form solution
- Implementation of the Adjoint method to evaluate the sensitivity of dynamic responses modeled by the discrete representation method
- Application of the proposed stochastic topology optimization method to achieve optimal solutions satisfying probabilistic constraints on stochastic responses of structural systems



Acknowledgements

Prof. Junho Song

Derya Deniz
Hyun-woo Lim
Nolan Kurtz
Roselyn Jihyen Kim
Reece Otsuka

Prof. Glaucio H. Paulino

Arun Gain
Tomas Zegard
Sofie Leon
Daniel Spring
Evgueni Filipov
Heng Chi
Maryam Eidini

Prof. Adeildo Soares Ramos Jr. Prof. Ivan Menezes

**Tam Nguyen
Lauren Beghini
Cameron Talischi**

- Karol Fellowship
- National Science Foundation

Question and Comments?





Performance of sensitivity methods

- Input stochastic process

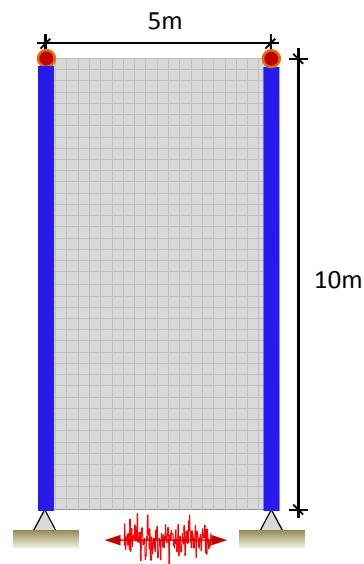
$$f(t) = \mathbf{s}(t)^T \mathbf{v} \quad s_i(t) = \exp[-2.4\pi(t - t_i)] \sin[3.2\pi(t - t_i)] H(t - t_i) / \|\mathbf{s}(t)\|$$

- Failure event

$$E_f = u_0 - \left(\frac{(\mathbf{a}(t_0, \tilde{\boldsymbol{\rho}})_{Left}^T + \mathbf{a}(t_0, \tilde{\boldsymbol{\rho}})_{Right}^T) \mathbf{v}}{2} \right) \leq 0$$

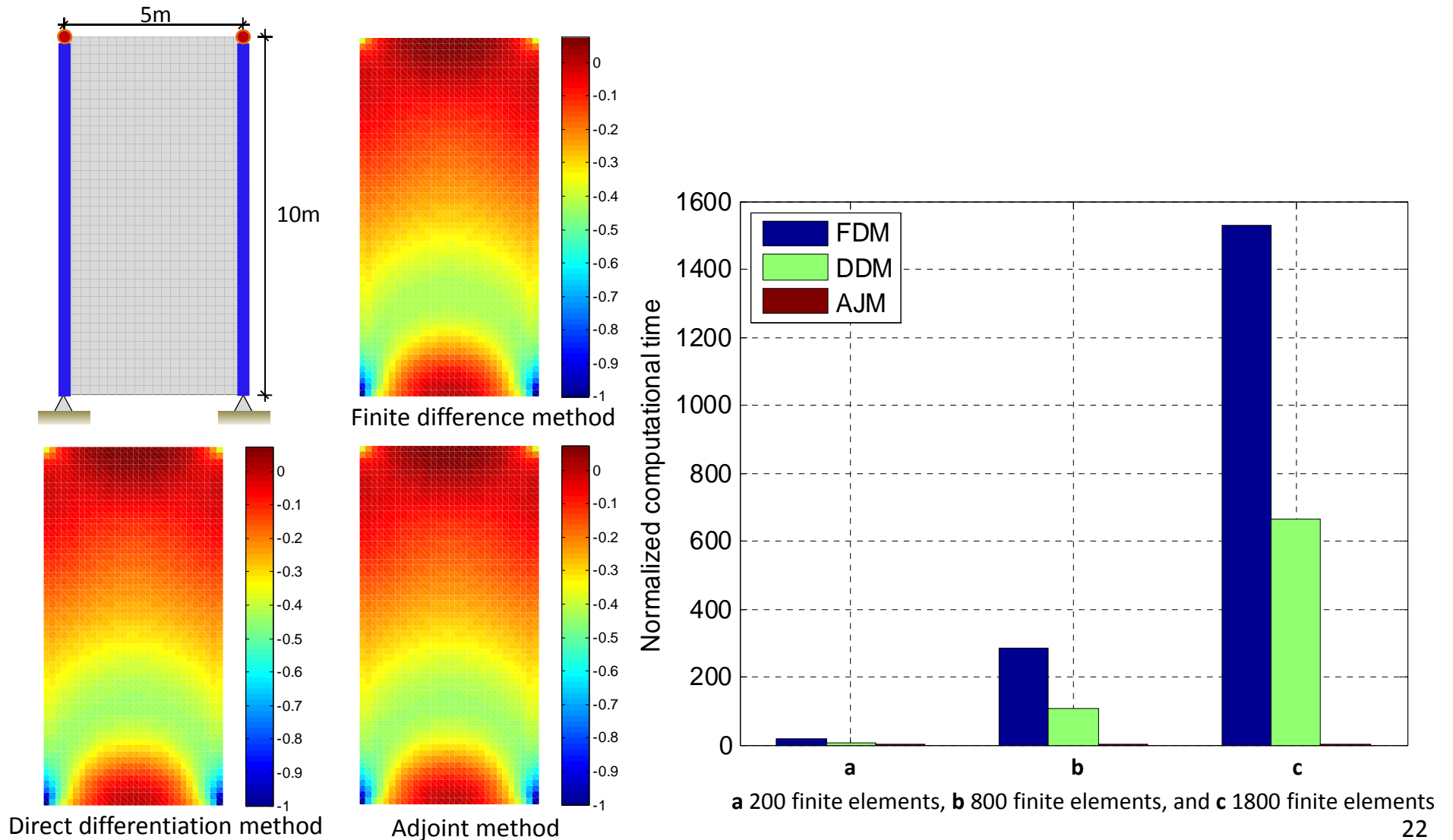
- Sensitivity

$$\frac{\partial \beta(u_0, t_0, \tilde{\boldsymbol{\rho}})}{\partial d_e}$$



E	21,000Mpa
ρ	2,400kg/m ³
Thickness	0.10 m
Column	0.35m x 0.35m
Time, t₀	7 sec
Threshold values u₀	0.02
Initial.Volf	0.5

Performance of sensitivity methods-cont'd



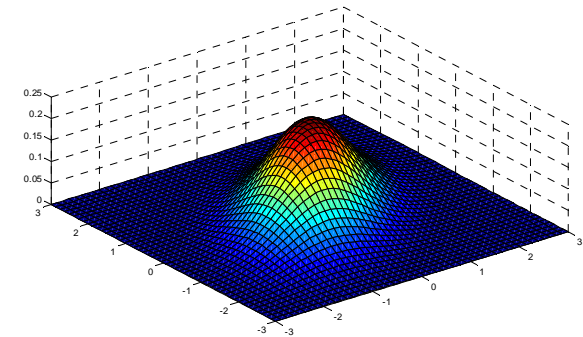
Reliability-Based Design Optimization

- Deterministic design optimization (DO)

$$\min_{\mathbf{d}} f_{obj}(\mathbf{d})$$

$$s.t \quad g_i(\mathbf{d}) > 0, \quad i = 1, \dots, n_c$$

$$\mathbf{d}^{lower} \leq \mathbf{d} \leq \mathbf{d}^{upper}$$

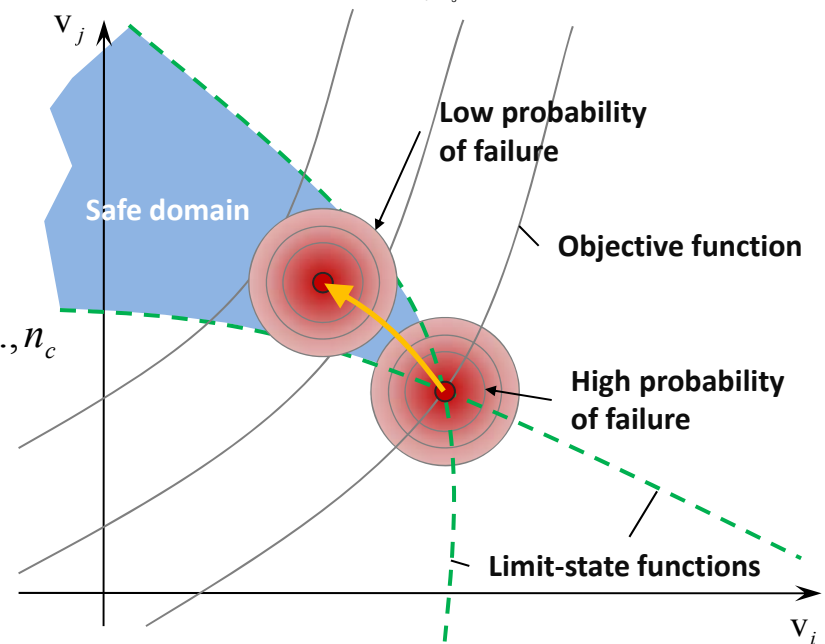


- Reliability-based design optimization (RBDO)

$$\min_{\mathbf{d}, \boldsymbol{\mu}_X} f_{obj}(\mathbf{d}, \boldsymbol{\mu}_X)$$

$$s.t \quad P(E_{sys}) = P[\cup \cap g_i(\mathbf{d}, \boldsymbol{\mu}_X) \leq 0] \leq P_{sys}^{target}, \quad i = 1, \dots, n_c$$

$$\mathbf{d}^{lower} \leq \mathbf{d} \leq \mathbf{d}^{upper}, \quad \boldsymbol{\mu}^{lower} \leq \boldsymbol{\mu}_X \leq \boldsymbol{\mu}^{upper}$$



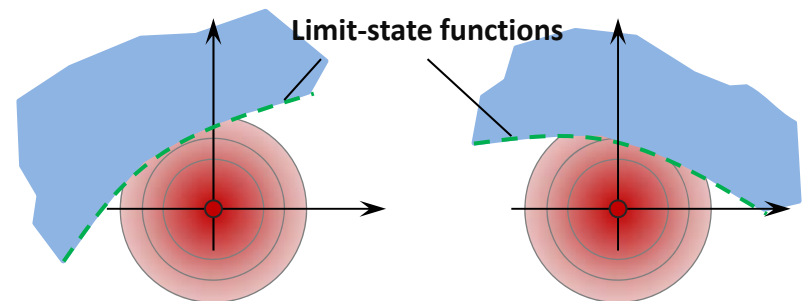
System Reliability-Based Design Optimization

□ Component Reliability Based Design Optimization (CRBDO)

$$\min_{\mathbf{d}, \boldsymbol{\mu}_X} f_{obj}(\mathbf{d}, \boldsymbol{\mu}_X)$$

$$s.t \quad P[g_i(\mathbf{d}, \boldsymbol{\mu}_X) \leq 0] \leq P_f^{target}, \quad i = 1, \dots, n_c$$

$$\mathbf{d}^{lower} \leq \mathbf{d} \leq \mathbf{d}^{upper}, \quad \boldsymbol{\mu}^{lower} \leq \boldsymbol{\mu}_X \leq \boldsymbol{\mu}^{upper}$$

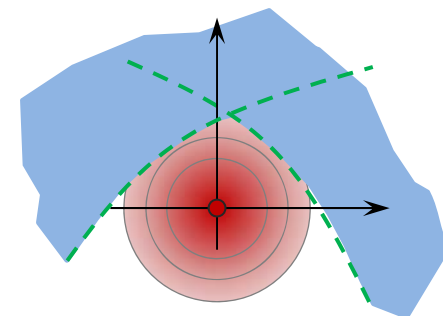


□ System Reliability Based Design Optimization (SRBDO)

$$\min_{\mathbf{d}, \boldsymbol{\mu}_X} f_{obj}(\mathbf{d}, \boldsymbol{\mu}_X)$$

$$s.t \quad P(E_{sys}) = P[\bigcup \bigcap g_i(\mathbf{d}, \boldsymbol{\mu}_X) \leq 0] \leq P_{sys}^{target}, \quad i = 1, \dots, n_c$$

$$\mathbf{d}^{lower} \leq \mathbf{d} \leq \mathbf{d}^{upper}, \quad \boldsymbol{\mu}^{lower} \leq \boldsymbol{\mu}_X \leq \boldsymbol{\mu}^{upper}$$

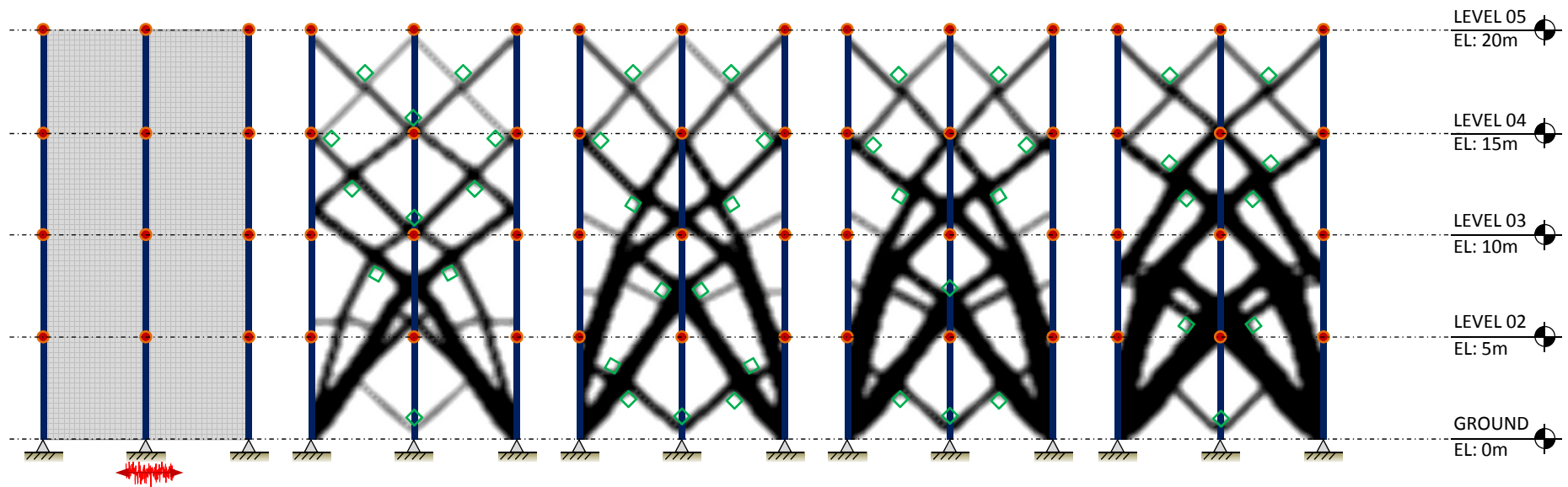


MSR method

(Song and Kang 2009, Kang et al. 2012)

Optimal topologies

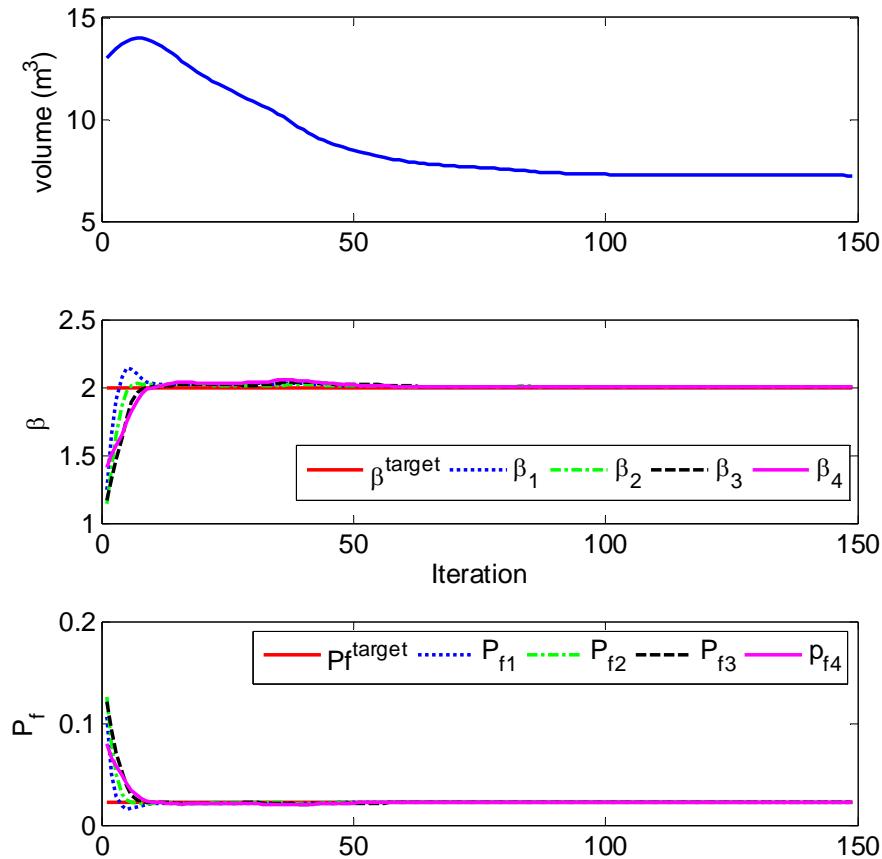
- Varying target failure probabilities



	A ($\Phi_0=700$)	B ($\Phi_0=700$)	C ($\Phi_0=700$)	D ($\Phi_0=700$)
β^{target}	1.4 = ($P_f=8.1\%$)	β^{target} 1.7 = ($P_f=4.5\%$)	β^{target} 2.0 = ($P_f=2.3\%$)	β^{target} 2.3 = ($P_f=1.1\%$)
Volume	4.95 m ³ (24.7%)	Volume 6.15 m ³ (30.8%)	Volume 7.19 m ³ (35.9%)	Volume 8.34 m ³ (41.7%)

Convergence and Dynamic response

□ Convergence history



□ Dynamic response comparison

