New Developments in Tail-Equivalent Linearization method for Nonlinear Stochastic Dynamics

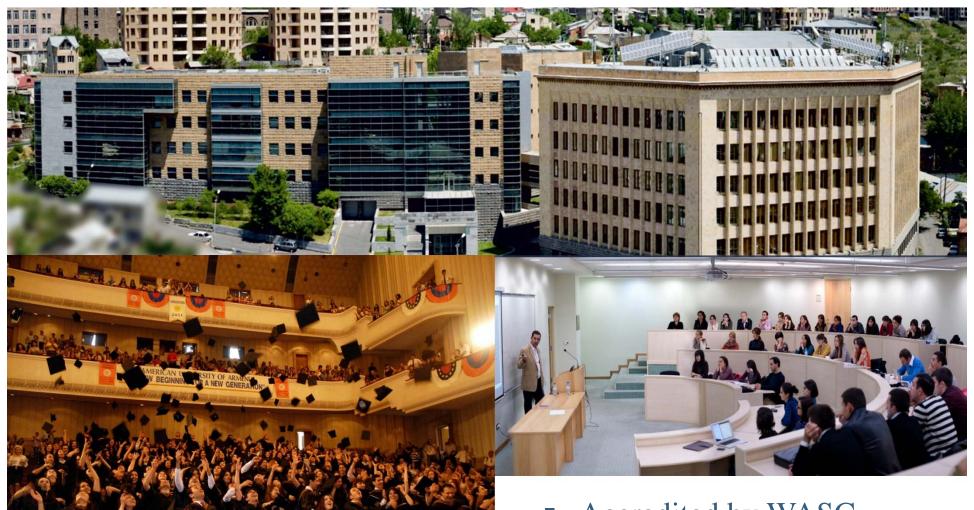
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Acknowledgement:

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The American University of Armenia



- Accredited by WASC
- Affiliated with UC

Motivation

- Stochasticity and nonlinearity are essential considerations in assessing the reliability of structural and mechanical systems under extreme loads, e.g.
 - Inelastic response to earthquake ground motion
 - Response to wave loading under material and/or geometric nonlinearities
 - Response to turbulent wind
- Existing methods of nonlinear stochastic dynamic analysis are restricted to special cases, or are not well suited for reliability analysis – hence the need for a new method.

Outline

- Methods for nonlinear stochastic dynamic analysis
- □ The equivalent linearization method (ELM)
- Basic elements of TELM:
 - Characterization of linear systems
 - The first-order reliability method (FORM)
 - Discretization of stochastic excitation
- ☐ The tail-equivalent linearization method (TELM)
- Characteristics of TELM
- Applications of TELM
- Challenges and limitation of TELM
- Concluding remarks

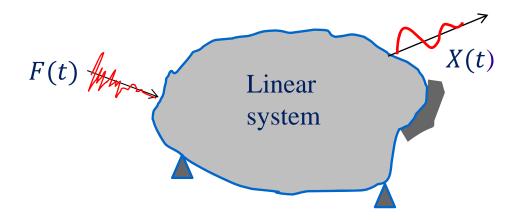
Methods for nonlinear stochastic dynamic analysis

- Classical methods
 - Fokker-Planck equation
 - Stochastic averaging
 - Moment/cumulant closure
 - Perturbation
- The equivalent linearization method (ELM)
- Monte Carlo simulation

Equivalent linearization methods (ELM)

- Approximates the nonlinear response in terms of the response of an "equivalent" linear system (Caughey 1963).
- □ The ELS is determined by minimizing a measure of discrepancy between nonlinear and linear responses:
 - Conventional ELM minimize the variance of the error between nonlinear and linear responses; requires the assumption of a distribution, typically Gaussian (e.g., Atalik & Utku 1976; Wen 1976).
 - Minimize the difference in mean up-crossing rates at a selected threshold (Casciati et al. 1993).
 - Minimize higher moments of the error (Naess 1995).
 - TELM set the tail probability of the linear response equal to the first-order approximation of the tail probability of the nonlinear response (Fujimura and Der Kiureghian 2007).

Characterization of a linear system



- For an input-output pair (F(t), X(t)), a stable linear system is completely defined by either of the following:
 - h(t)= impulse response function (IRF), i.e., response to $F(t)=\delta(t)$
 - $H(\omega)=$ frequency response function (FRF), i.e., amplitude of steady-state response to $F(t)=\exp(i\omega t)$

The first-order reliability method (FORM)

- An approximate method for solving time-invariant reliability problems:
 - * $\mathbf{x} = \text{vector of random variables}$ $g(\mathbf{x}) = \text{limit-state function: } \{g(\mathbf{x}) \leq 0\} = \text{failure event}$ $p_f = \Pr[g(\mathbf{x}) \leq 0]$ probability of failure



• $\mathbf{u} = \mathbf{u}(\mathbf{x})$ transformation to standard normal space $G(\mathbf{u}) = g(\mathbf{x}(\mathbf{u}))$ limit-state function in transformed space $\mathbf{u}^* = \min \arg\{\|\mathbf{u}\| \mid G(\mathbf{u}) = 0\}$ design point $\beta = \|\mathbf{u}^*\|$ reliability index $p_f \approx \Phi(-\beta)$, FORM approximation

Discrete representation of a stochastic process

General form for a zero-mean Gaussian process

$$F(t) = \mathbf{s}(t) \cdot \mathbf{u}$$

$$\mathbf{s}(t) = [\mathbf{s}_{t}(t) - \mathbf{s}_{t}(t)]$$

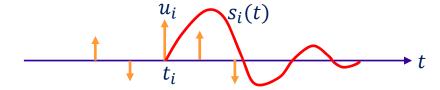
 $\mathbf{s}(t) = [s_1(t) \cdots s_n(t)]$ vector of deterministic basis functions

 $\mathbf{u} = [u_1 \cdots u_n]$ vector of standard normal random variables

Time-domain discretization (modulated filtered white noise)

$$s_i(t) = q(t)h_f(t - t_i)$$

 $h_f(\cdot)=$ impulse response function of a linear filter



Discrete representation of a stochastic process

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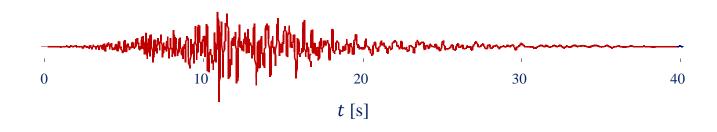
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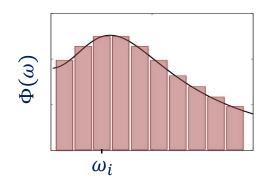
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Frequency-domain discretization (stationary process)

$$F(t) = \sum_{i=1}^{n/2} \sigma_i [u_i \sin(\omega_i t) + \bar{u}_i \cos(\omega_i t)]$$

$$s_i(t) = \sigma_i \sin(\omega_i t), \ \bar{s}_i(t) = \sigma_i \cos(\omega_i t)$$





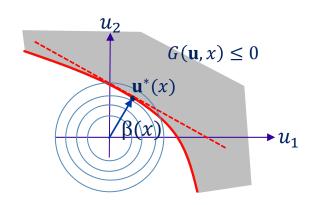
FORM solution of stochastic dynamic problems

Definitions:

- $F(t) = \mathbf{s}(t) \cdot \mathbf{u}$ discretized stochastic excitation
- $X(t, \mathbf{u}) = \text{response to discretized stochastic excitation}$
- $\Pr(x < X(t, \mathbf{u})) = \text{tail probability for threshold } x \text{ at time } t$

Reliability formulation:

- $G(\mathbf{u}, x) = x X(t, \mathbf{u})$
- $\Pr(x < X(t, \mathbf{u})) = \Pr(G(\mathbf{u}, x) \le 0)$
- $\mathbf{u}^*(x) = \arg\min\{\|\mathbf{u}\| \mid G(\mathbf{u}, x) = 0\}$
- $\beta(x) = \|\mathbf{u}^*(x)\|$
- $\Pr(x < X(t, \mathbf{u})) \approx \Phi(-\beta(x))$ FORM approx. of tail probability

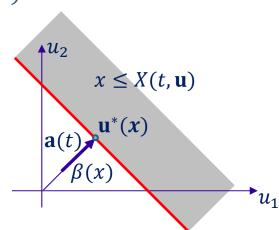


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- $Pr(x < X(t, \mathbf{u})) = tail probability for threshold x$
- Reliability formulation the case of linear system
 - $X(t, \mathbf{u}) = \mathbf{a}(t) \cdot \mathbf{u}, \quad a_i(t) = \text{response to } s_i(t)$
 - $G(\mathbf{u}, x) = x \mathbf{a}(t) \cdot \mathbf{u}$
 - $\mathbf{u}^*(x) = \frac{x\mathbf{a}(t)}{\|\mathbf{a}(t)\|^2}$ $\beta(x) = \frac{x}{\|\mathbf{a}(t)\|}$

 - $\Pr(x < X(t, \mathbf{u})) = \Phi(-\beta(x))$



Identification of the linear system

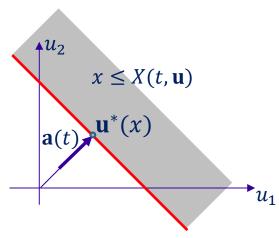
 Given the design point, one can identify the linear system (for the particular input-output pair)

$$\mathbf{u}^* \rightarrow \mathbf{a}(t) = \frac{x\mathbf{u}^*}{\|\mathbf{u}^*\|^2}$$

Time-domain analysis:

Solve for h(t) in system of equations

$$\sum_{j=1}^{n} h(t-t_j) s_i(t_j) \Delta t = a_i(t), \ i = 1, \dots, n$$



Identification of linear system

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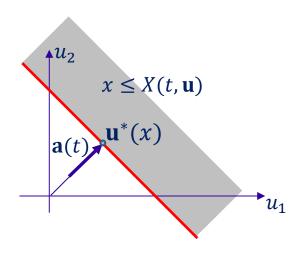
$$\mathbf{u}^* \rightarrow \mathbf{a}(t) = \frac{x\mathbf{u}^*}{\|\mathbf{u}^*\|^2}$$

Frequency-domain analysis:

$$|H(\omega_i)| = \frac{\sqrt{a_i(t)^2 + \bar{a}_i(t)^2}}{\sigma_i}$$

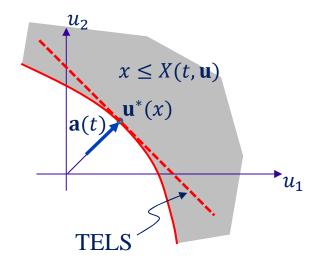
$$\theta_i = \tan^1 \left[\frac{a_i(t)}{a_i(t)}\right]$$

$$H(\omega_i) = |H(\omega_i)| \exp(i\theta_i)$$



The tail-equivalent linearization method (TELM)

- For selected threshold x and time t, formulate the tail probability problem in terms of the limit-state function $G(\mathbf{u},t)=x-X(t,\mathbf{u})$
- \Box Find the design point $\mathbf{u}^*(x)$
- Find the gradient vector of the tangent plane $\mathbf{a}(t) = \frac{x\mathbf{u}^*}{\|\mathbf{u}^*\|^2}$
- Identify the tail-equivalent linear system (TELS) in terms of its IRF h(t) or its FRF $H(\omega)$



For the given threshold x and time t, the tail probability of the TELS response = first-order approximation of the tail probability of the nonlinear system response



Tail-Equivalent Linearization Method (TELM)

As opposed to ELM and other linearization methods,
 TELM is a non-parametric method.



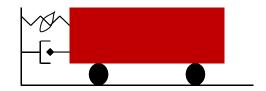
There is no need to define a parameterized linear system.

The TELS is identified numerically in terms of its IRF h(t) or its FRF $H(\omega)$.

- The deign-point excitation $F^*(t) = \mathbf{s}(t) \cdot \mathbf{u}^*$ represents the most likely realization of the stochastic excitation to give rise to the event $\{x \leq X(t, \mathbf{u})\}$
- Example:

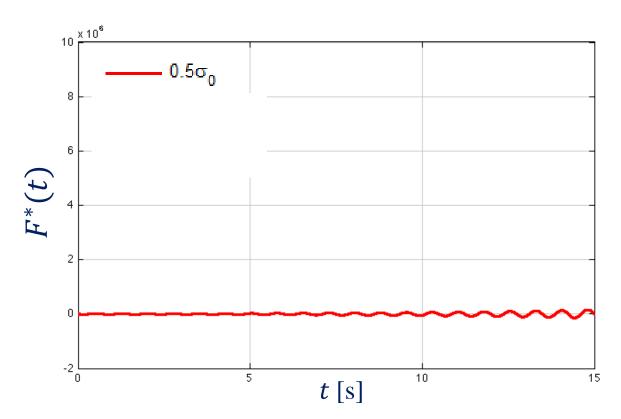
$$m\ddot{X} + c\dot{X} + k[\alpha X + (1 - \alpha)Z] = F(t)$$

$$\dot{Z} = -\gamma |\dot{X}| |Z|^{n-1} Z - \eta |Z|^n \dot{X} + A\dot{X}$$

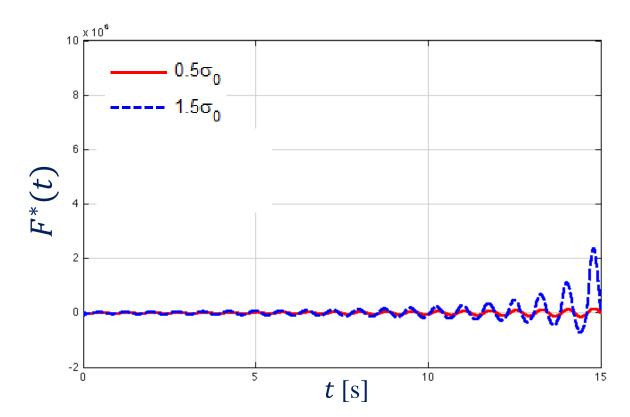


$$m=3E5$$
kg; $c=251$ kNs/m $k=2.1E4$ kN/m, $\alpha=0.1$ $\gamma=\eta=1/2\sigma_0, n=3, A=1$ $F(t)$ white noise, $S=1$ m $^2/s^3$ rad $\sigma_0=\pi Sm^2/ck$

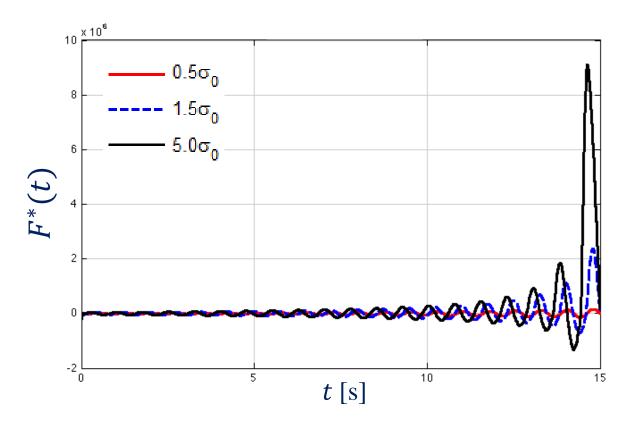
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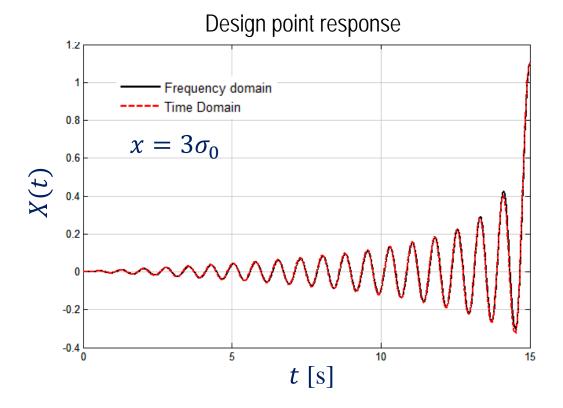
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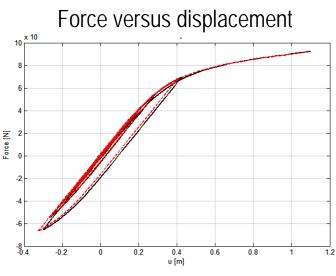


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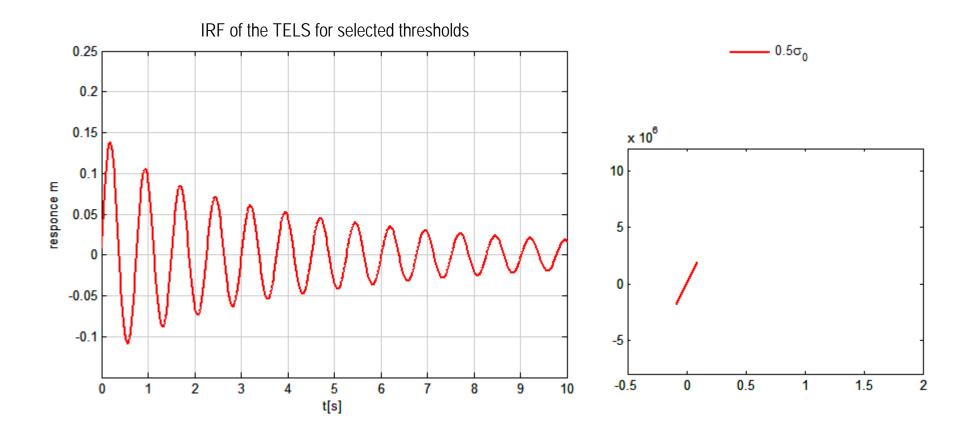
The deign-point response $X(t, \mathbf{u}^*)$ represents the most likely realization of the response trajectory leading to $X(t, \mathbf{u}) = x$.





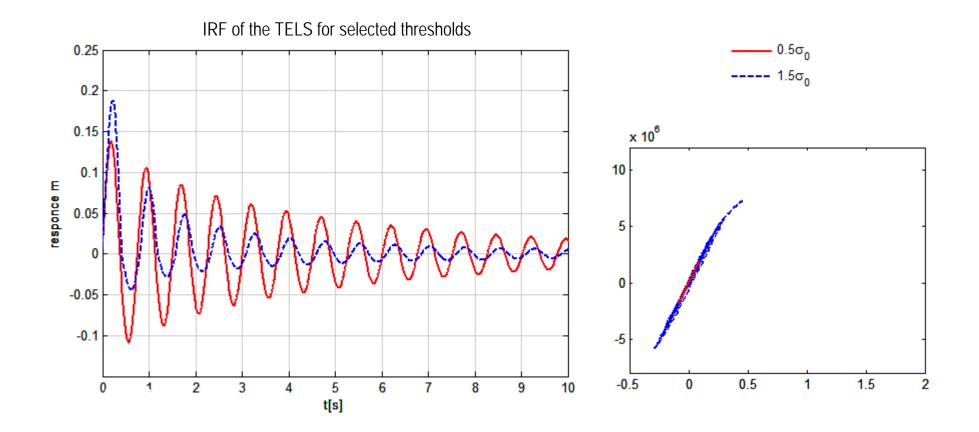
■ The TELS strongly depends on the selected threshold:

$$h(t) \rightarrow h(t,x), H(\omega) \rightarrow H(\omega,x)$$



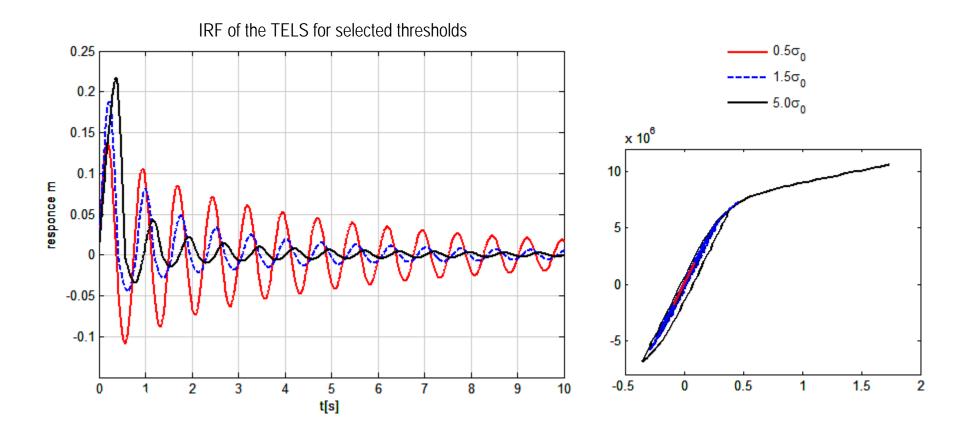
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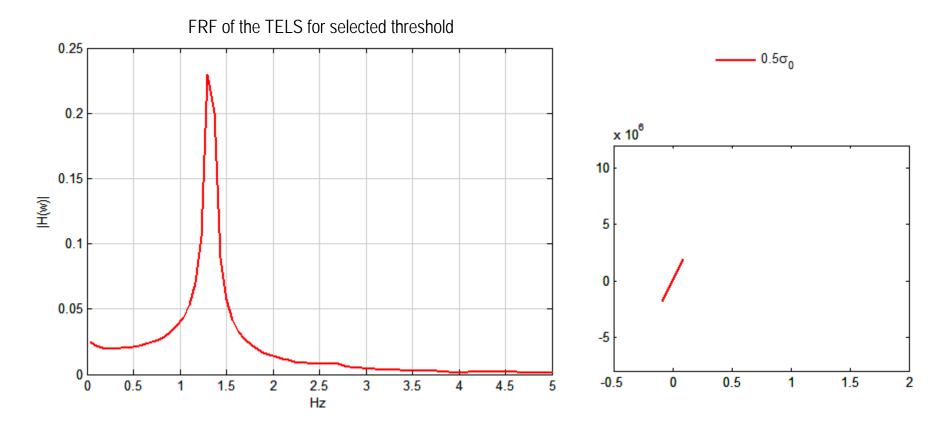
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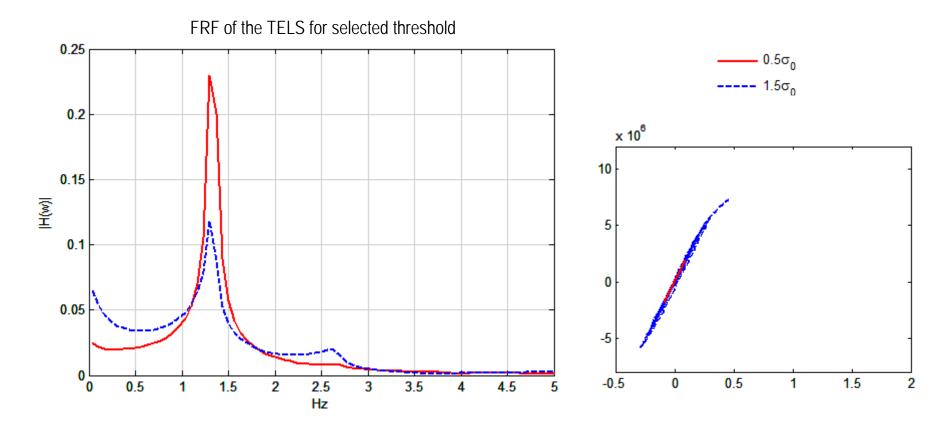
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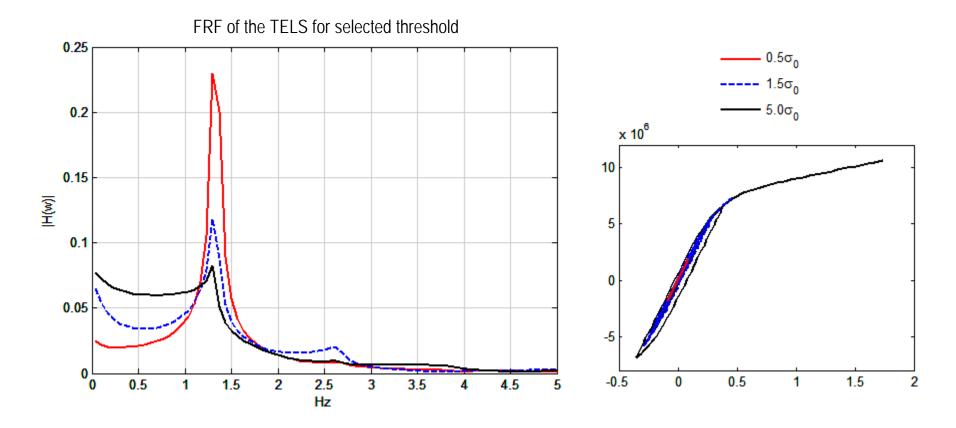
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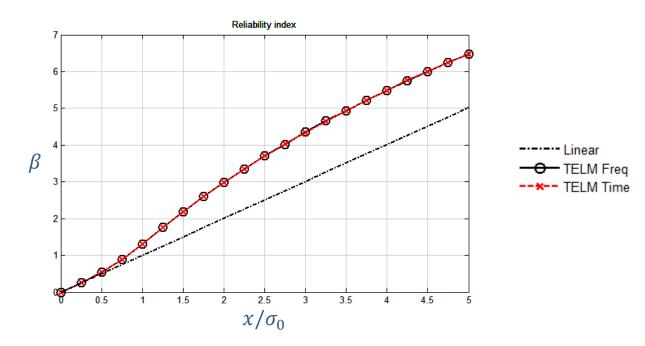
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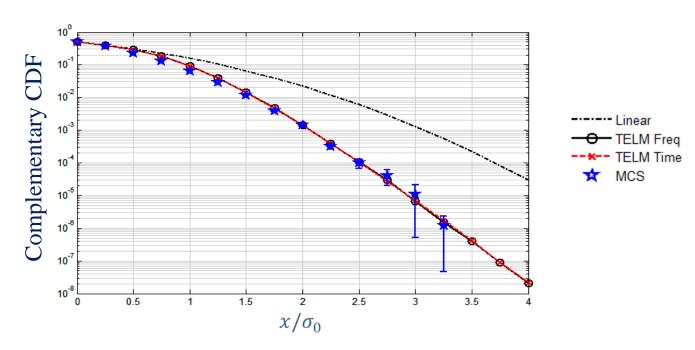
Because of TELS's dependence on the threshold, TELM captures the non-Gaussian distribution of the nonlinear response.

$$\Pr[x \le X(t, u)] \approx \Phi[-\beta(x)]$$



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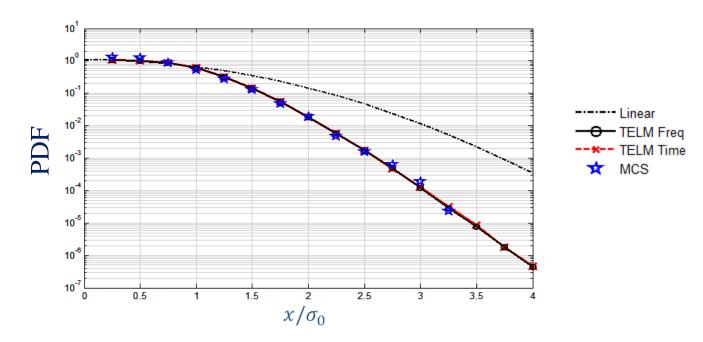
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Characteristics of TELM and TELS

■ Because of TELS's dependence on the threshold, TELM captures the *non-Gaussian distribution* of the nonlinear response.

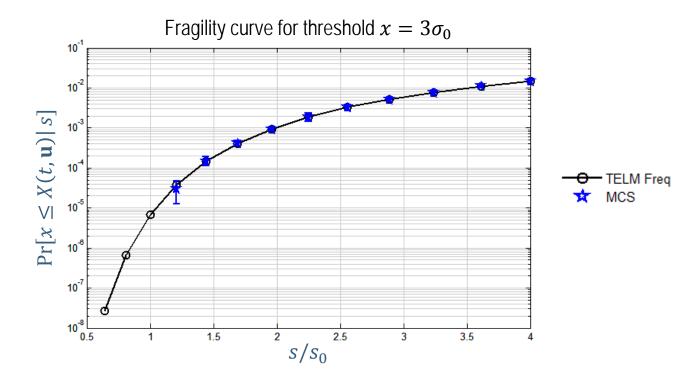
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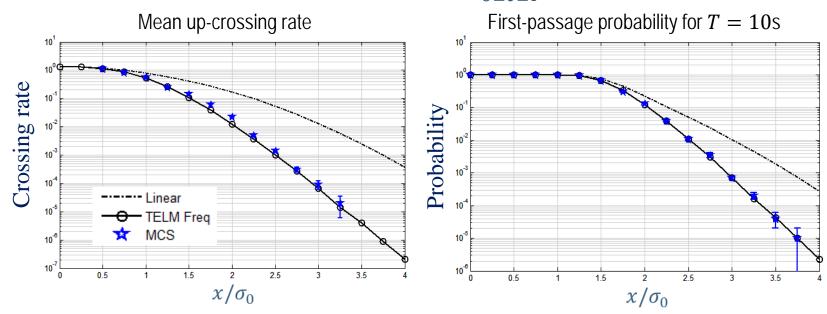
TELS is invariant of the scaling of the excitation, i.e., h(t,x) and $H(\omega,x)$ for excitation sF(t) are invariant of s.



Useful property for developing fragility curves:



- For stationary response, TELS is invariant of time t. Thus, TELSs determined for one time point are sufficient to evaluate all statistical properties of the response, e.g.,
 - Point-in-time distribution $Pr[x \le X(t, \mathbf{u})]$
 - Mean up-crossing rate $v^+(x)$
 - First-passage probability $\Pr[x \leq \max_{0 \leq t \leq T} |X(t)|]$



- For non-stationary excitation with smooth evolution in time, TELS at a critical time can be used as an approximation for all times.
 - Evolutionary TELM (Broccardo/Der Kiureghian 2013)
- Evolutionary input-output for a linear system

$$\Phi_{XX}(\omega, t) = |M(\omega, t)|^2 \Phi_{FF}(\omega)$$

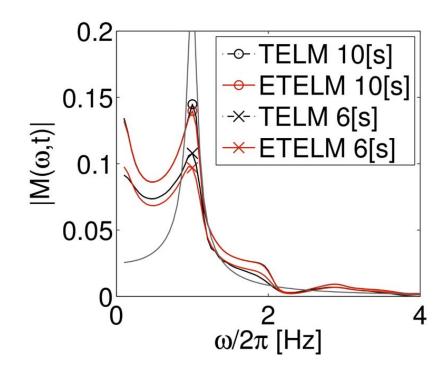
$$M(\omega, t) = \int_0^t A(\omega, t - \tau) h(\tau) e^{-i\omega t} d\tau$$

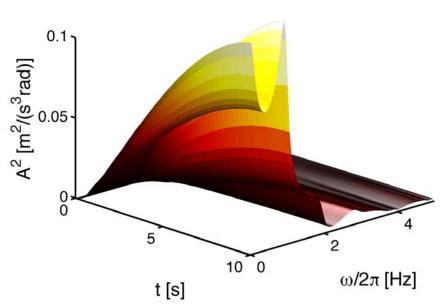
ETELM

$$M(\omega, t, x) \approx \int_0^t A(\omega, t - \tau) h_{TELS}(\tau, x) e^{-i\omega t} d\tau$$

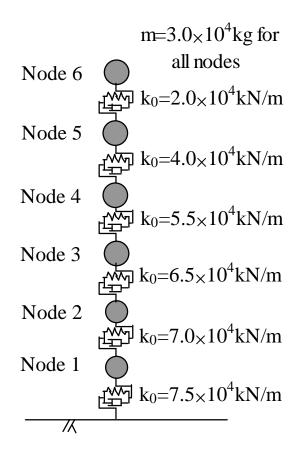
 $h_{TELS}(t,x)$ determined at a critical point in time, e.g., peak intensity of the excitation.

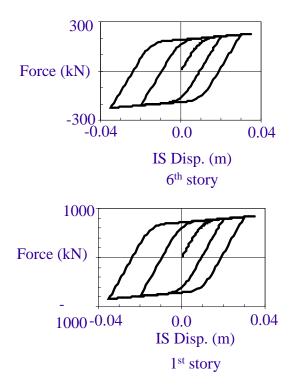
- For non-stationary excitation with smooth evolution in time, TELS at a critical time can be used as an approximation for all times.
- Example response to uniformly modulated process





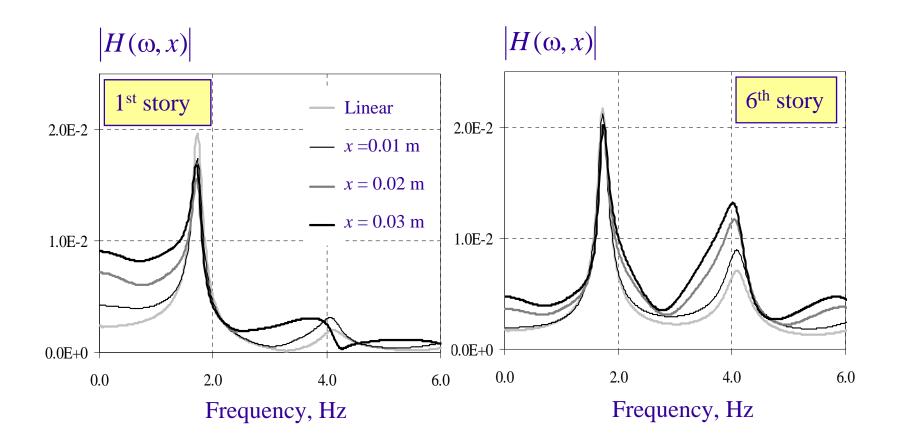
□ TELM is easily extended to MDoF systems — number of random variables remain the same.



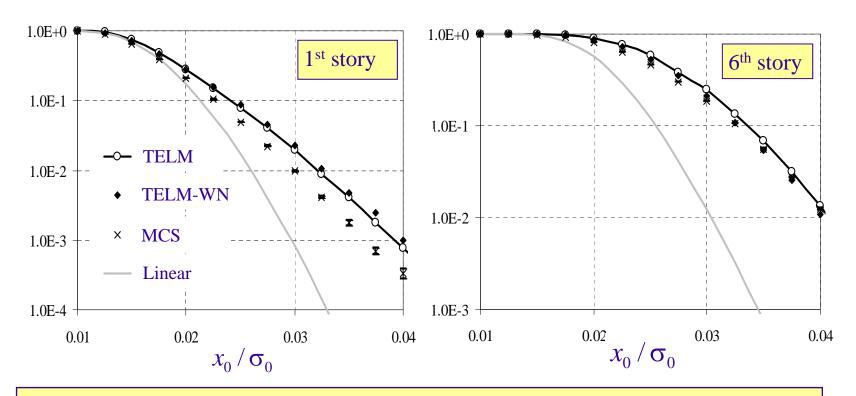


Smooth bilinear hysteresis model

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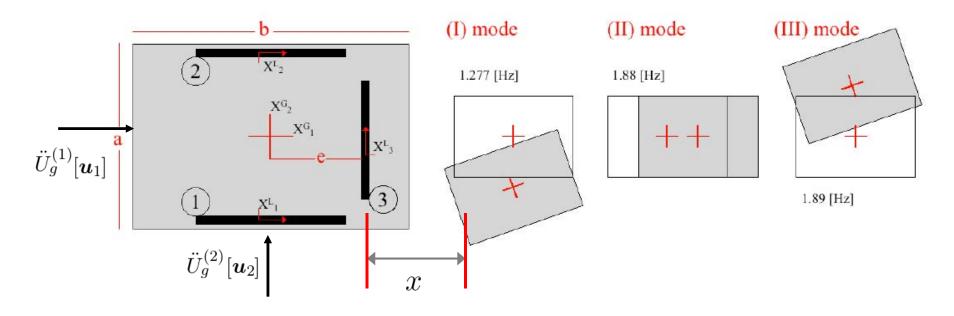


First-passage probability (10s duration)

Multi-component (SI) excitations

$$\mathbf{F}(t) = \begin{bmatrix} \mathbf{s}^{(1)}(t)\mathbf{u}^{(1)} \\ \vdots \\ \mathbf{s}^{(m)}(t)\mathbf{u}^{(m)} \end{bmatrix}$$

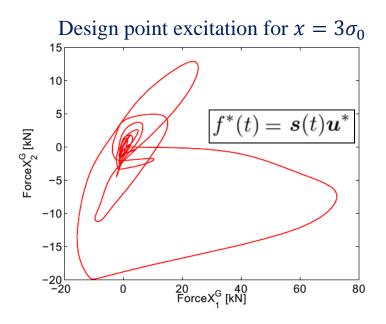
a separate TELS is identified for each input component.

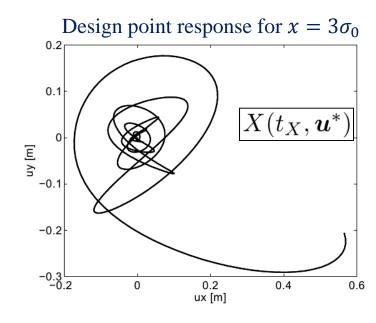


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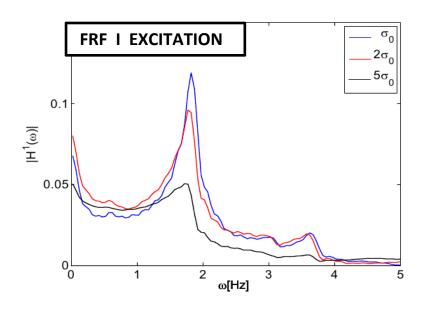


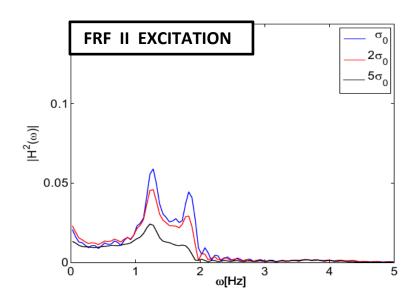


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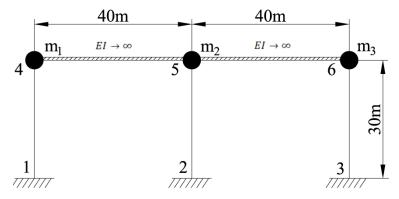
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Multiply-supported inelastic system subject to spatially varying

ground motions:



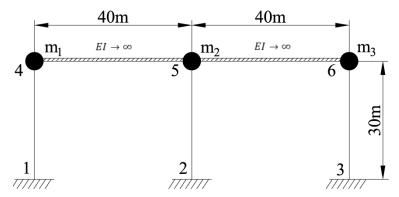
$$D_k(t) = \sum_{p=1}^{n/2} [A_{pk} \cos(\omega_p t) + B_{pk} \sin(\omega_p t)], k = 1, ..., m$$

m = number of support DOFs

 A_{pk} , B_{pk} = Fourier coefficients, zero-mean Gaussian random variables, independent for different frequencies, correlated for same frequency different supports

Multiply-supported inelastic system subject to spatially varying

ground motions:



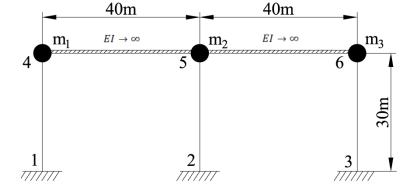
Cases considered:

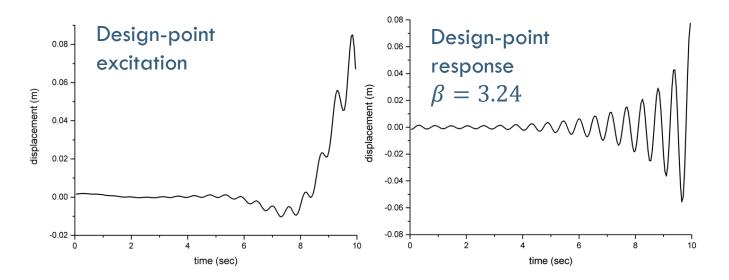
- 1. Uniform ground motions
- 2. Totally incoherent ground motions
- 3. Wave-passage and partial incoherence
- 4. Case 3 with variable soil conditions

Multiply-supported inelastic system subject to spatially varying

ground motions:

Uniform ground motions





Multiply-supported inelastic system subject to spatially varying

40m

ground motions:

Totally incoherent ground motions

Design-point

excitation

2

time (sec)

0.08

0.06

0.04

0.02

0.00

-0.02

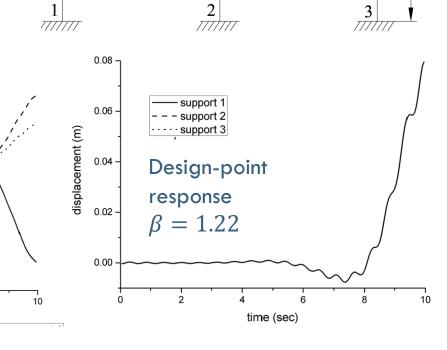
-0.04

-0.06

-0.08 -0.10

-0.12 -0.14

displacement (m)



40m

 $EI \rightarrow \infty$

 m_2

 m_3

30m

Multiply-supported inelastic system subject to spatially varying

40m

ground motions:

Wave passage and partial incoherence

Design-point

8

time (sec)

excitation

0.12 -

0.10

0.08

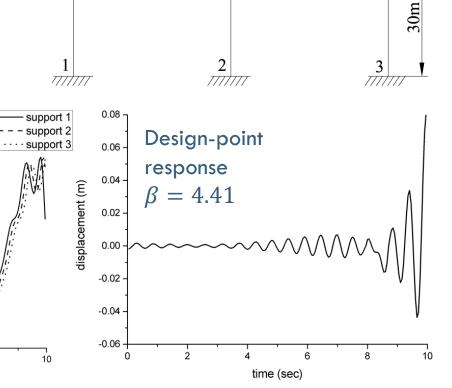
0.04

0.02

0.00

-0.02 -

displacement (m)



40m

 $EI \rightarrow \infty$

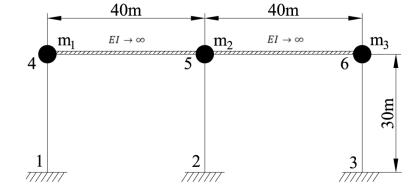
 m_3

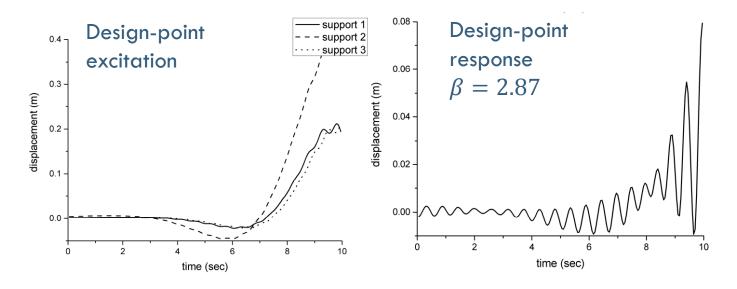
 m_2

Multiply-supported inelastic system subject to spatially varying

ground motions:

Wave passage and partial incoherence with variable soil

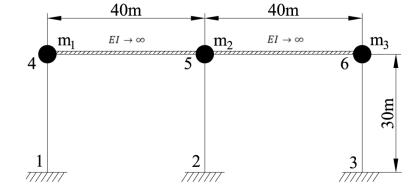


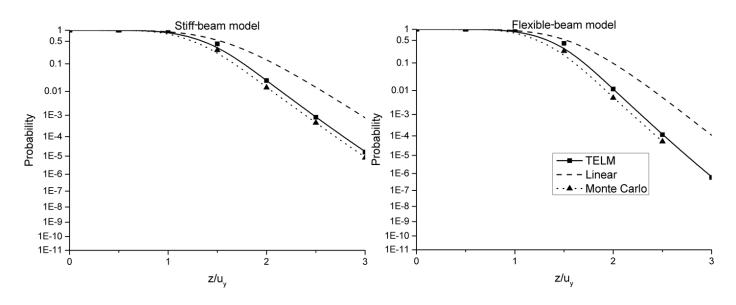


Multiply-supported inelastic system subject to spatially varying

ground motions:

First-passage probability for Case 3





Challenges and limitations of TELM

- TELM requires repeated computations of $X(t, \mathbf{u})$ and $\nabla_{\mathbf{u}}X(t,\mathbf{u})$ for selected values of \mathbf{u} (typically around 10 times) to find the design point \mathbf{u}^* . We use the Direct Differentiation Method (DDM) for this purpose.
- □ The nonlinear response must be continuously differentiable must use smooth or smoothened constitutive laws.
- The limit-state surface must be well behaving. TELM does not work well for strongly stiffening systems (e.g., Duffing oscillator with a strong cubic term) or when nonlinearity involves abrupt changes in the system behavior.
- As of now, TELM is not applicable to degrading systems.

Concluding remarks

- □ TELM is an alternative equivalent linearization method for nonlinear stochastic dynamic analysis.
- □ TELM: Is a non-parametric method

Captures non-Gaussian distribution of nonlinear response

Offers superior accuracy for tail probabilities

Is particularly convenient for fragility analysis

Can be applied to stationary or non-stationary response

Can be applied to MDoF systems, multi-component excitations, variable support motions

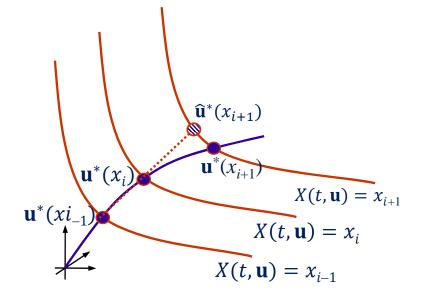
- TELM requires continuous differentiability of the nonlinear response.
- As with other linearization methods, the accuracy of TELM depends on the nature of the nonlinearity.

Thank you!

Determination of the design point

- lterative algorithms for solving $\mathbf{u}^*(x) = \arg\min\{\|\mathbf{u}\| \mid G(\mathbf{u}, x) = 0\}$ require repeated computations of $X(t, \mathbf{u})$ and $\nabla_{\mathbf{u}} X(t, \mathbf{u})$.
- For an ordered sequence of thresholds $x_1 < x_2 < \cdots < x_n$, use extrapolated starting points:

$$\widehat{\mathbf{u}}^{*}(x_{i+1}) = \\ \mathbf{u}^{*}(x_{i}) + \lambda \frac{\mathbf{u}^{*}(x_{i}) - \mathbf{u}^{*}(x_{i-1})}{\|\mathbf{u}^{*}(x_{i}) - \mathbf{u}^{*}(x_{i-1})\|}$$

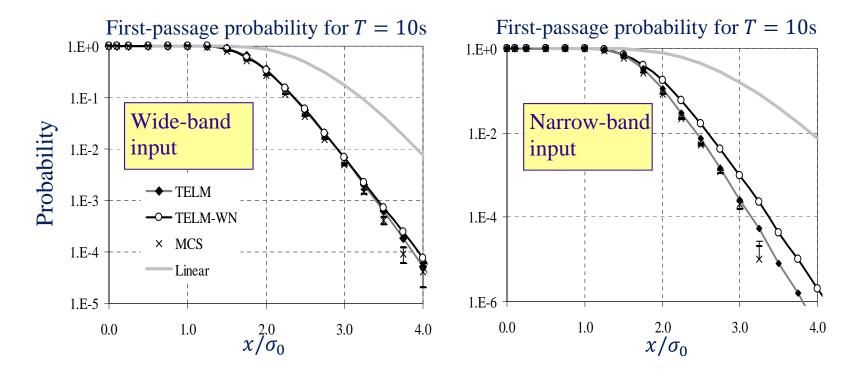


Characteristics of TELM and TELS

For broad-band excitations, the TELS is insensitive to the frequency content.

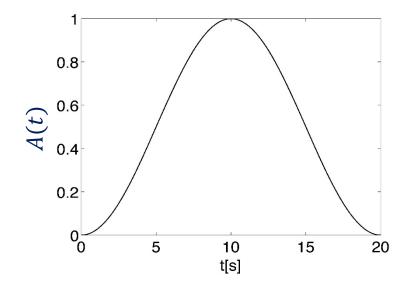


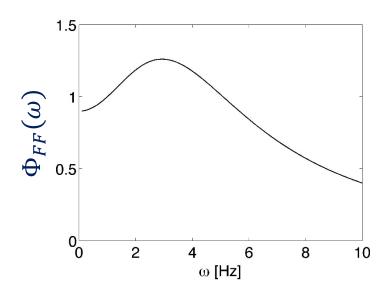
TELS for response to white noise can be used as an approximation for response to *non-white excitations*



Characteristics of TELM and TELS

- For non-stationary processes with smooth evolution in time, TELS at a critical time can be used as an approximation for all times.
- Example response to uniformly modulated process





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