

# Set-valued stochastic processes in vibration analysis

Bernhard Schmelzer

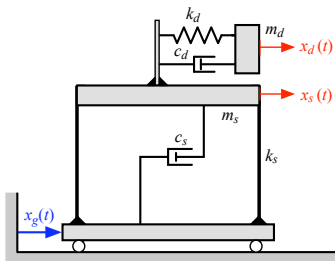
joint work with Christoph Adam and Michael Oberguggenberger

Leopold-Franzens-Universität Innsbruck

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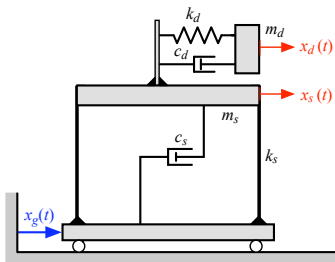
Consider slender structure

- modelled by single-degree-of-freedom (SDOF) oscillator with mass  $m_s$ , viscous damping parameter  $c_s$  and stiffness  $k_s$



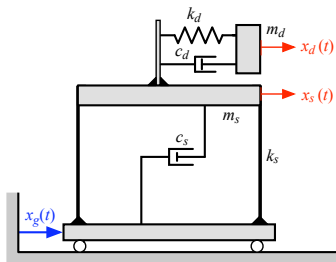
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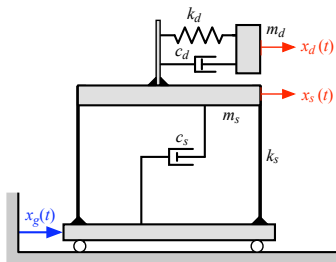
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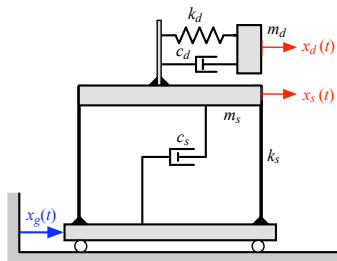
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- weak damping
- ground excitation  $x_g$  (earthquake)
- leads to structural vibrations with large amplitudes (displacement  $x_s$ )



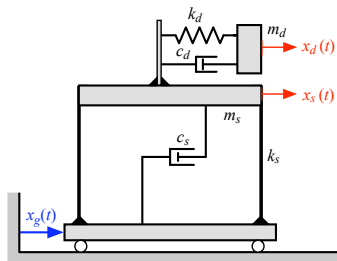
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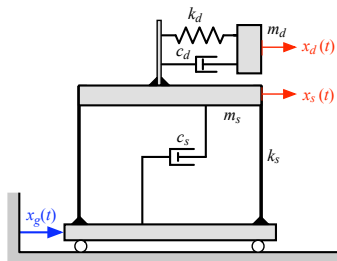
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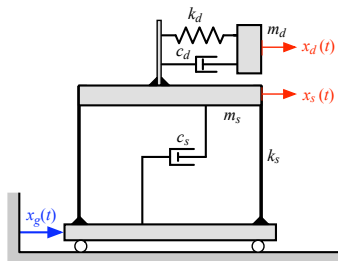
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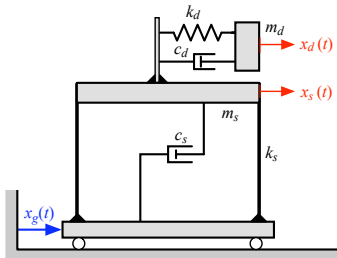
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- kinetic energy is transferred from structure to TMD
- optimal tuning of TMD depending on type of excitation
- possible in theory, very difficult in practice → parameter uncertainty



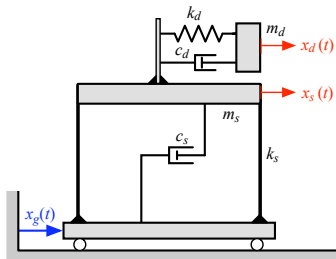
## Combined structure-TMD system

- modelled by two-degrees-of-freedom oscillator  
→ system of ODEs



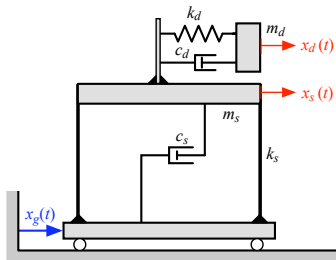
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- modelled by two-degrees-of-freedom oscillator  
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- modelling ground acceleration  $\ddot{x}_g$  by white noise  
→ system of stochastic differential equations
- modelling parameter uncertainty by random sets  
→ set-valued processes as output



$$dx_t = f(t, x_t)dt + G(t, x_t)dw_t$$

with

- $t_0 \leq t \leq \bar{t} < \infty$ ,
- $\{w_t\}_{t \geq t_0}$  being an  $m$ -dimensional Wiener process on a probability space  $(\Omega_w, \Sigma_w, P_w)$ ,
- initial value  $x_{t_0}$  and coefficients  $f$  and  $G$ :

$$\begin{aligned}x_{t_0} &: \Omega_w \rightarrow \mathbb{R}^d, & \omega_w &\mapsto x_{t_0}(\omega_w), \\f &: [t_0, \bar{t}] \times \mathbb{R}^d \rightarrow \mathbb{R}^d, & (t, x) &\mapsto f(t, x), \\G &: [t_0, \bar{t}] \times \mathbb{R}^d \rightarrow \mathbb{R}^{d \times m}, & (t, x) &\mapsto G(t, x).\end{aligned}$$

$$dx_{t,\mathbf{a}} = f(t, \mathbf{a}, x_{t,\mathbf{a}})dt + G(t, \mathbf{a}, x_{t,\mathbf{a}})dw_t$$

with **uncertain parameters**  $\mathbf{a} \in \mathbb{A} \subseteq \mathbb{R}^p$  and

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$$\begin{aligned} x_{t_0} &: \mathbb{A} \times \Omega_w \rightarrow \mathbb{R}^d, & (\mathbf{a}, \omega_w) &\mapsto x_{t_0,\mathbf{a}}(\omega_w), \\ f &: [t_0, \bar{t}] \times \mathbb{A} \times \mathbb{R}^d \rightarrow \mathbb{R}^d, & (t, \mathbf{a}, x) &\mapsto f(t, \mathbf{a}, x), \\ G &: [t_0, \bar{t}] \times \mathbb{A} \times \mathbb{R}^d \rightarrow \mathbb{R}^{d \times m}, & (t, \mathbf{a}, x) &\mapsto G(t, \mathbf{a}, x). \end{aligned}$$

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- This leads to the map

$$x : [t_0, \bar{t}] \times \mathbb{A} \times \Omega_w \rightarrow \mathbb{R}^d, (t, a, \omega_w) \mapsto x_{t,a}(\omega_w)$$

which is a **stochastic process** on  $[t_0, \bar{t}] \times \mathbb{A}$  and  $(\Omega_w, \Sigma_w, P_w)$ .



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which is a **stochastic process** on  $[t_0, \bar{t}] \times \mathbb{A}$  and  $(\Omega_w, \Sigma_w, P_w)$ .

- Under certain conditions it can be shown that  $x$  has a version
  - whose sample paths are **continuous** on  $[t_0, \bar{t}] \times \mathbb{A}$ ,
  - which is  $\mathcal{B}([t_0, \bar{t}]) \otimes \mathcal{B}(\mathbb{A}) \otimes \Sigma_w$ -**measurable**.

- To model the uncertainty of  $a$  we use a **random compact set**

$$A : \Omega_{\mathbb{A}} \rightarrow \mathcal{K}'(\mathbb{A})$$

- on a probability space  $(\Omega_{\mathbb{A}}, \Sigma_{\mathbb{A}}, P_{\mathbb{A}})$
- with non-empty compact values being subsets of  $\mathbb{A}$

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- with non-empty compact values being subsets of  $\mathbb{A}$
- Defining measurability condition: for all  $B \in \mathcal{B}(\mathbb{R}^d)$  it holds that

$$A^{-}(B) = \{\omega_{\mathbb{A}} : A(\omega_{\mathbb{A}}) \cap B \neq \emptyset\} \in \Sigma_{\mathbb{A}}.$$

- Define the set-valued map

$$X : (t, \omega) \mapsto \{x_{t,a}(\omega_w) : a \in A(\omega_{\mathbb{A}})\}$$

where  $(t, \omega) \in [t_0, \bar{t}] \times \Omega$  and  $\Omega$  denotes the product space

$$(\Omega, \Sigma, P) = (\Omega_{\mathbb{A}} \times \Omega_w, \Sigma_{\mathbb{A}} \otimes \Sigma_w, P_{\mathbb{A}} \otimes P_w).$$

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- **Is this a set-valued process (measurability)?**
- **What are its properties?**

- $X$  is a **set-valued process** on  $[t_0, \bar{t}]$  and the completed probability space  $(\Omega, \overline{\Sigma}^P, \overline{P})$  with values in  $\mathcal{K}'(\mathbb{R}^d)$ , i.e., for all  $t \in [t_0, \bar{t}]$  and  $B \in \mathcal{B}(\mathbb{R}^d)$  it holds that

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- all sample functions of  $X$  are **continuous** with respect to the Hausdorff-metric on  $\mathcal{K}'(\mathbb{R}^d)$ ,

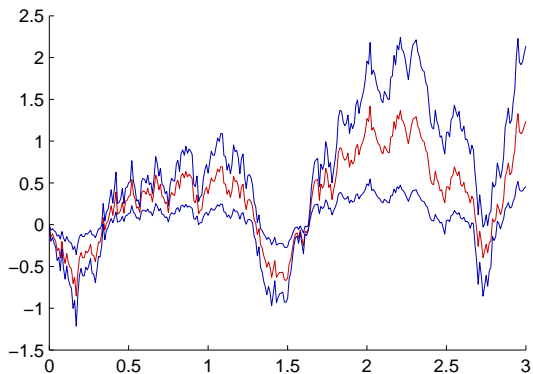


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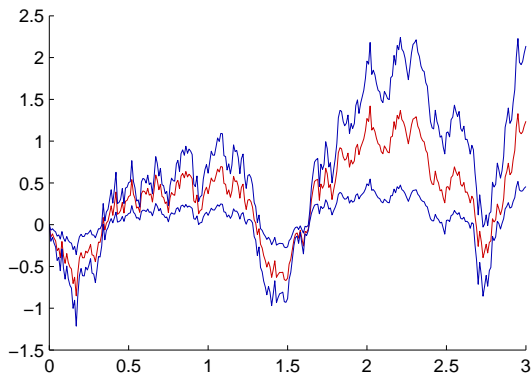
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- all sample functions of  $X$  are **continuous** with respect to the Hausdorff-metric on  $\mathcal{K}'(\mathbb{R}^d)$ ,
- $X$  is **measurable** with respect to the product- $\sigma$ -algebra  $\mathcal{B}([t_0, \bar{t}]) \otimes \overline{\Sigma}^P$ .

# Picture of a sample path

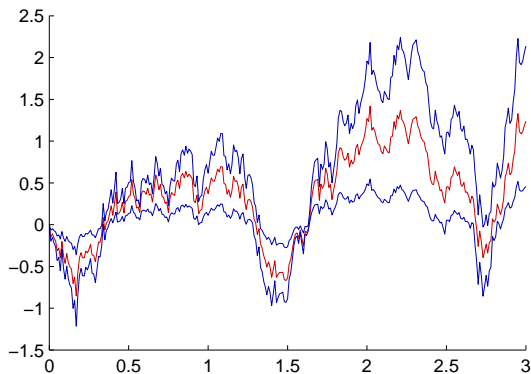


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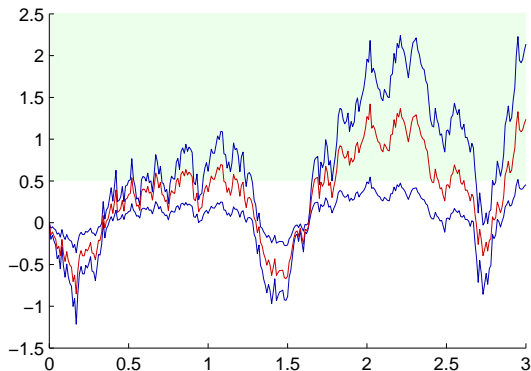
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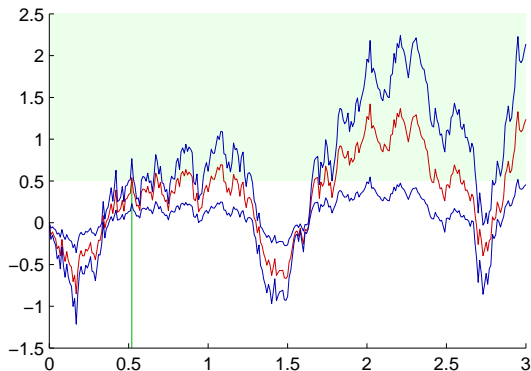
- blue lines: boundaries of sample path of set-valued process  $X$
- red line: sample path of a selection  $\xi$

# First entrance and inclusion times



When does  $\xi$  enter  $B$  for the first time?

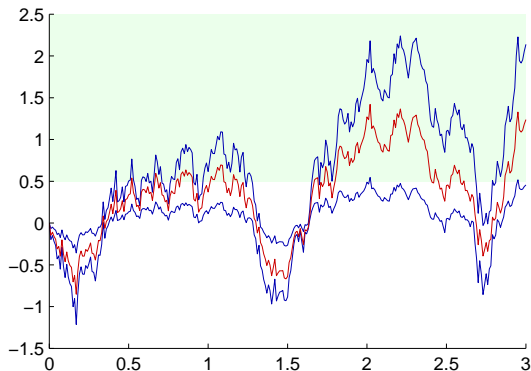
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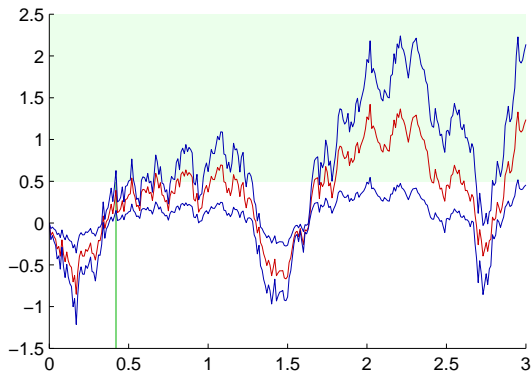
→ first entrance time  $\tau_{\xi}^B : \omega \mapsto \inf\{t : \xi_t(\omega) \in B\}$

# First entrance and inclusion times



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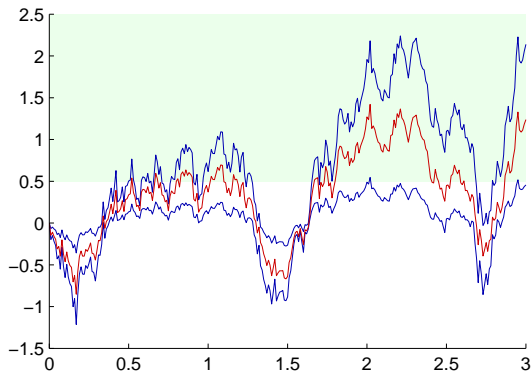


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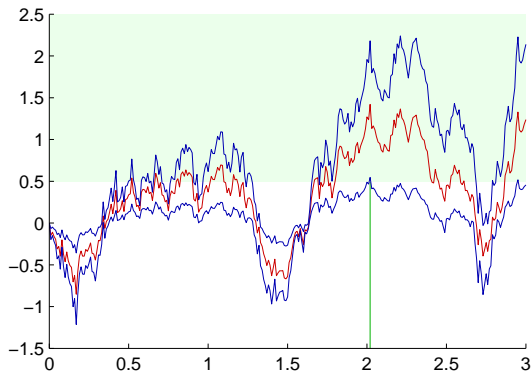


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Under certain conditions  $\underline{\tau}$  and  $\bar{\tau}$

- are random variables on  $(\Omega, \Sigma, P)$ ,

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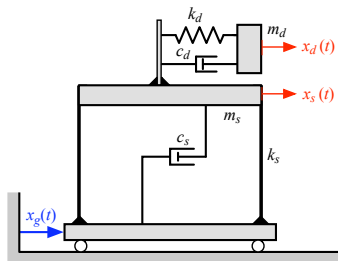
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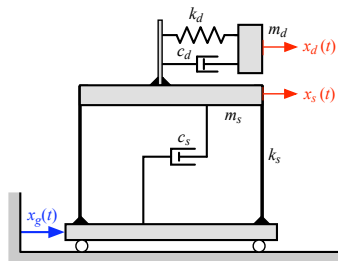
- are random variables on  $(\Omega, \Sigma, P)$ ,
- are even stopping times with respect to an appropriate filtration,
- can be attained by first entrance times of selection processes of  $X$ .

# TMD - Mechanical model



Defining

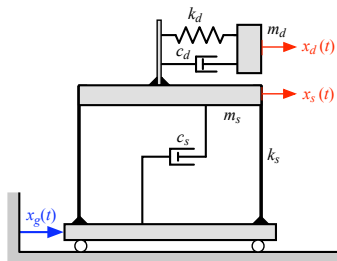
# TMD - Mechanical model



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- mass ratio:  $\mu = \frac{m_d}{m_s} \ll 1$

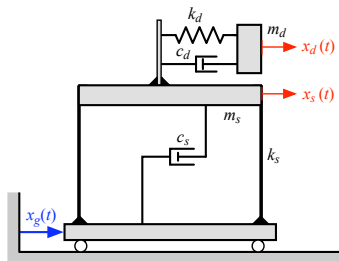
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- non-dimensional damping coefficients:  $\zeta_s = \frac{c_s}{2\omega_s m_s}$ ,  $\zeta_d = \frac{c_d}{2\omega_d m_d}$

The coupled equations of motion can be written as a 4-dimensional linear system of SDEs of first order:

$$dy_t = M y_t dt + G dw_t, \quad y_0 = 0$$

where

$$y_t = \begin{pmatrix} x_s \\ x_d \\ \dot{x}_s \\ \dot{x}_d \end{pmatrix}, \quad G = \begin{pmatrix} 0 \\ 0 \\ -1 \\ -1 \end{pmatrix}$$

$$M = \begin{pmatrix} 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \\ -\omega_s^2 - \omega_d^2 \mu & \omega_d^2 \mu & -2\zeta_s \omega_s - 2\zeta_d \omega_d \mu & 2\zeta_d \omega_d \mu \\ \omega_s^2 & -\omega_d^2 & 2\zeta_d \omega_d & -2\zeta_d \omega_d \end{pmatrix}$$

- **fixed parameters:**  $\mu$ ,  $\zeta_s$  and  $\omega_s = 2\pi/T$  for different periods  $T$

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- **uncertain parameters:**  $a = (\zeta_d, \omega_d)$
- **optimal values**  $\bar{a} = (\bar{\zeta}_d, \bar{\omega}_d)$  under white noise excitation:

$$\bar{\zeta}_d = \sqrt{\frac{\mu(1 - \mu/4)}{4(1 + \mu)(1 - \mu/2)}}, \quad \bar{\omega}_d = \frac{\sqrt{1 - \mu/2}}{1 + \mu} \cdot \omega_s$$

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- Assessment for both parameters: **The probability that the parameter differs from its optimal value by more than 40% is at most 0.01.**

$$P_i(|a_i - \bar{a}_i| > 0.4\bar{a}_i) \leq 0.01$$

Modelling uncertainty by **Tchebychev random sets**

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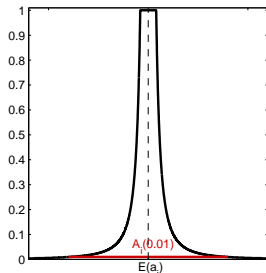
- Tchebychev's inequality:  $P(|a_i - E(a_i)| > c) \leq \frac{V(a_i)}{c^2}$



Modelling uncertainty by **Tchebychev random sets**

- Tchebychev's inequality:  $P(|a_i - E(a_i)| > c) \leq \frac{V(a_i)}{c^2}$
- implies random set

$$A_i : (0, 1] \rightarrow \mathcal{K}'(\mathbb{R}), c \mapsto \left[ E(a_i) - \sqrt{\frac{V(a_i)}{c}}, E(a_i) + \sqrt{\frac{V(a_i)}{c}} \right]$$

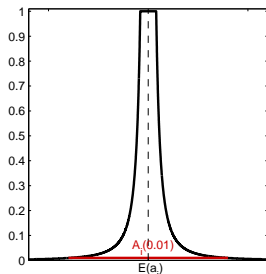


## Modelling uncertainty by Tchebychev random sets

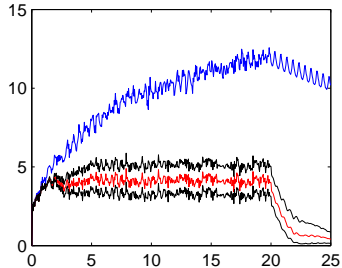
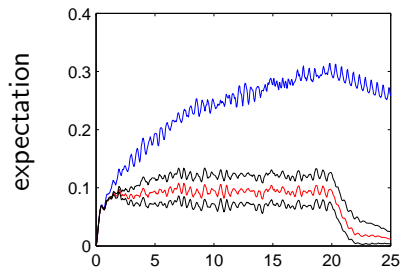
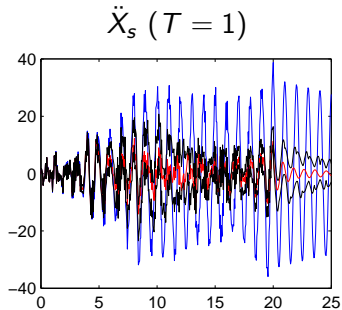
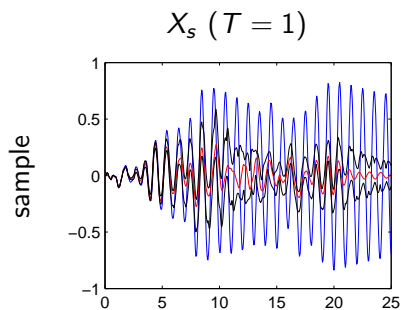
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- Random sets for  $a_1 = \zeta_d$  and  $a_2 = \omega_d$  are combined by random set independence to one random set  $A$  on  $\Omega_A = (0, 1]^2$  with values in  $\mathcal{K}'(\mathbb{R}^2)$



# TMD - Output: displacement and acceleration



# TMD - Output: first entrance and inclusion times

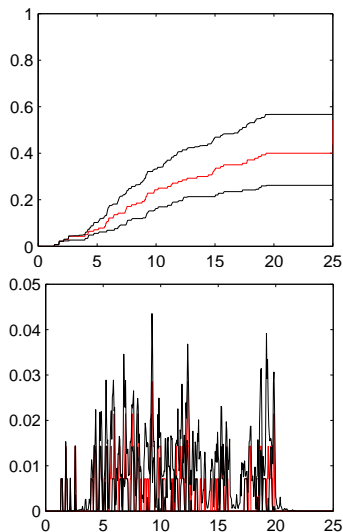
$$b = 0.5 \cdot \mathbb{E}(\sup_{t \in [t_0, \bar{t}]} |\tilde{X}_t|)$$
$$B = [b, \infty)$$

CDFs of  $\underline{\tau}^B$ ,  $\overline{\tau}^B$  and  $\tau_{X, \bar{a}}^B$

$$\overline{P}_t(B) = P(X_t \cap B \neq \emptyset)$$

$$\underline{P}_t(B) = P(X_t \subseteq B)$$

$$P_{\bar{a}, t}(B) = P(x_{t, \bar{a}} \in B)$$



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Reduction of displacement compared to displacement  $\tilde{x}_s$  of structure without TMD:

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- peak displacement: 
$$r_{\infty,a}(\omega_w) = \frac{\sup_{t \in [0, \bar{t}]} |x_{s,t,a}(\omega_w)|}{\sup_{t \in [0, \bar{t}]} |\tilde{x}_{s,t}(\omega_w)|}$$

# TMD - Output: reduction of displacement

Reduction of displacement compared to displacement  $\tilde{x}_s$  of structure without TMD:

- peak displacement:  $r_{\infty,a}(\omega_w) = \frac{\sup_{t \in [0, \bar{t}]} |x_{s,t,a}(\omega_w)|}{\sup_{t \in [0, \bar{t}]} |\tilde{x}_{s,t}(\omega_w)|}$
- mean square reduction:  $r_{2,a}(\omega_w) = \sqrt{\frac{\int_0^{\bar{t}} |x_{s,t,a}(\omega_w)|^2 dt}{\int_0^{\bar{t}} |\tilde{x}_{s,t}(\omega_w)|^2 dt}}$

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- two possible set-valued analogues:

$$R_*^{(1)}(\omega) = \{r_{*,a}(\omega_w) : a \in A(\omega_{\mathbb{A}})\}$$

$$R_*^{(2)}(\omega) = [\underline{R}_*(\omega), \overline{R}_*(\omega)]$$

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- it holds that  $R_*^{(1)} \subseteq R_*^{(2)}$

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