NARSIS Workshop

Training on Probabilistic Safety Assessment for Nuclear Facilities

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Methods for the derivation of fragility functions

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Introduction

- ***Fragility function*** **= Probability of reaching or exceeding a damage state given a level of loading**
  - Probabilistic tool (➔ uncertainty treatment)
  - To be coupled with probabilistic hazard assessment outcomes
  - Essential component of Probabilistic Safety Assessment

- **Fragility functions may be:**
  - Empirical (from observed past events)
  - Experiment-based
  - Analysis-based

  } *Most common in nuclear applications* (Experiment-based and Analysis-based)

➔ ***Current practical methods and assumptions?***

➔ ***Which types of uncertainty to consider?***

Outline

1. General principles
2. State-of-the-art of current methods
3. Selection of seismic intensity measures
4. Multi-variate fragility functions
5. Application
6. Beyond the lognormal assumption

General principles

➢ Notation

❑ Capitals → random variables

- IM = random Intensity Measure
- *im* → user-specified value (e.g. to define a threshold)

❑ Accents

- Median → $\overline{\blacksquare}$, e.g. $\overline{im}$
- Regression estimate → $\widehat{\blacksquare}$, e.g. $\widehat{EDP}$

General Principles

➢ Conditional probability

$$P_f(im) = P(DS \geq ds | IM = im)$$ **or** $$P_f(im) = P(EDP \geq EDP_{th} | IM = im)$$

$(DS \geq ds \Leftrightarrow EDP \geq EDP_{th})$

DS = Damage State

EDP = Engineering Demand Parameter

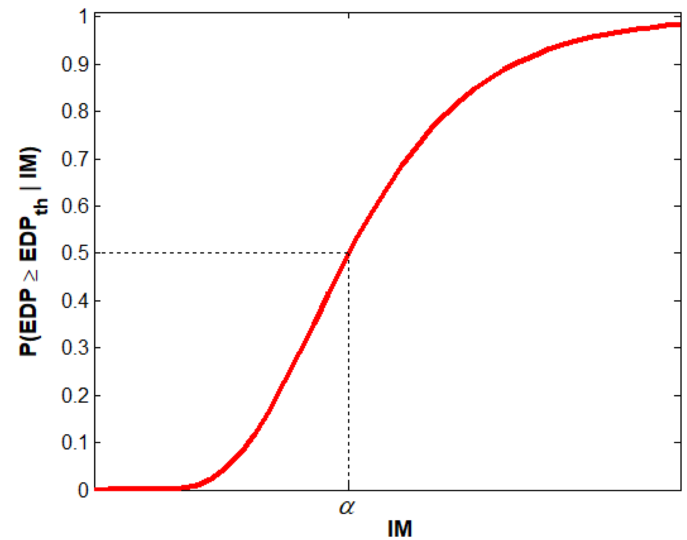
IM = Intensity Measure

➢ The lognormal assumption

$$P_f(im) = \Phi\left(\frac{\ln im - \ln \alpha}{\beta}\right)$$

α = median (= $\overline{im}$)

β = standard-deviation



General Principles

- **Two major types of uncertainty**
  - ***Aleatory:*** **inherent variability/randomness of physical quantities (e.g. variability of ground-motion for seismic analysis)**
  - ***Epistemic:*** **lack of complete knowledge, incomplete data or modelling assumptions**

Irreducible

Reducible with additional measures or testing

- **Main causes of epistemic uncertainties**
  - **In-situ uncertainty**
  - **Modelling uncertainty**
  - **Loading protocol uncertainty**
  - **Finite sample uncertainty**

Especially for experiment- or analysis-based fragility functions

General Principles

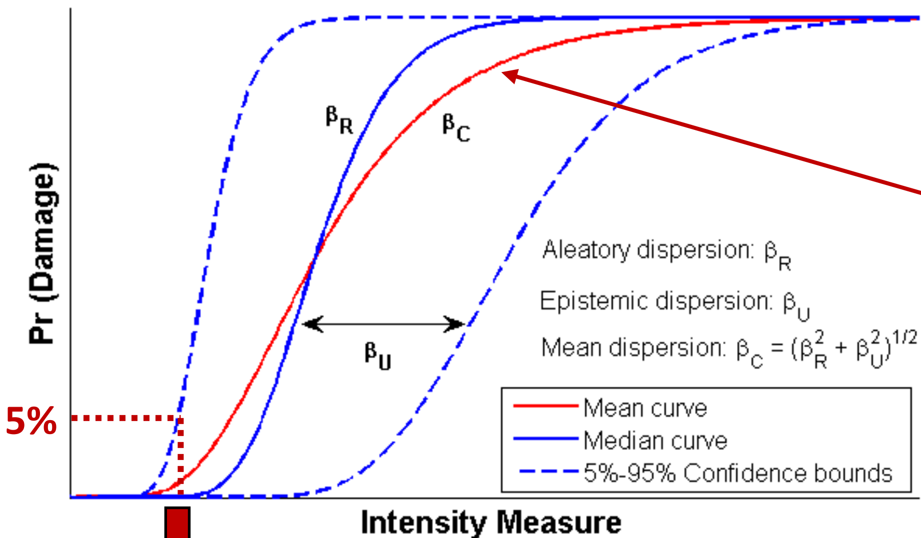
➢ The « double-lognormal » model

β_R = aleatory randomness

β_U = epistemic uncertainty

$$P_f(im) = \Phi\left(\frac{\ln im - \ln\alpha + \beta_U \Phi^{-1}(Q)}{\beta_R^2}\right)$$

***Kennedy et al.* (1980)**



Composite "Mean" curve

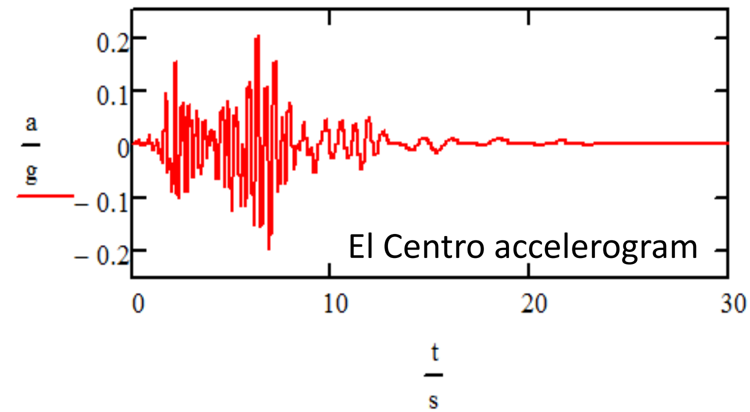
$$P_f(im) = \Phi\left(\frac{\ln im - \ln\alpha}{\sqrt{\beta_R^2 + \beta_U^2}}\right)$$

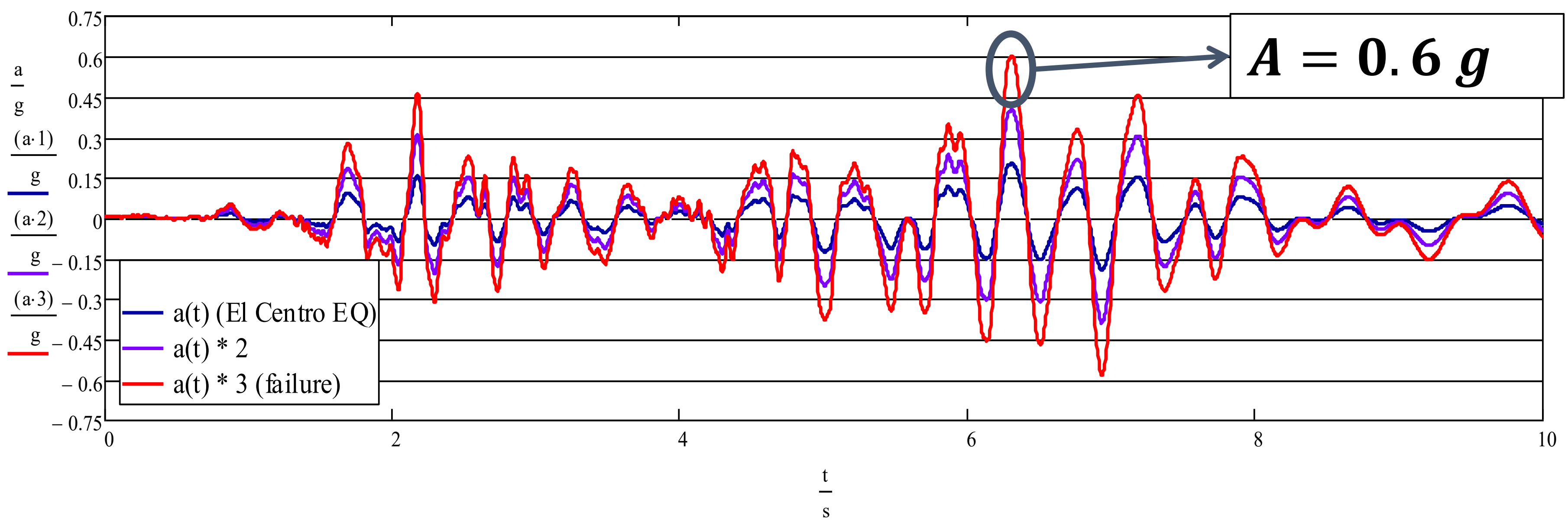
β_C

***IM_{HCLPF}** = IM level corresponding to a 5% probability of failure with a 95% confidence level (High Confidence Low Probability of Failure)*

Fragility can be viewed as the result of a scaling exercise

- **Random variable $\boldsymbol{A}: \boldsymbol{\Omega} \longmapsto \mathbb{R}$**
- **Sequence of EQ of increasing intensity:**
  $\boldsymbol{A}$: peak ground acceleration of the least intense EQ leading to failure of the SSC



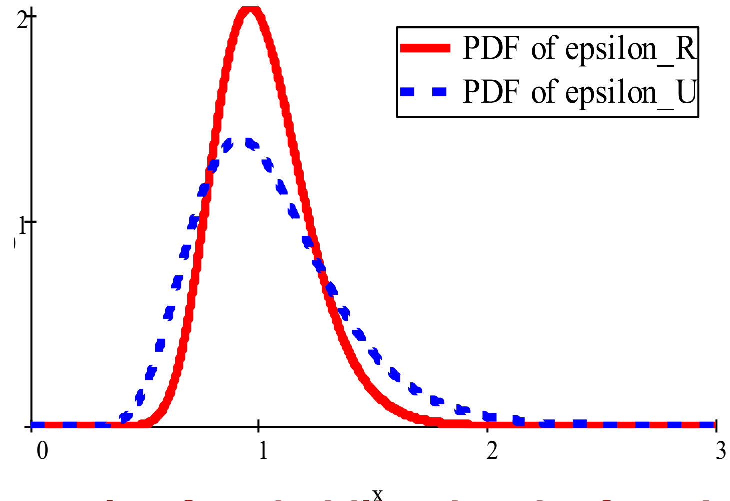


Double log-normal model
Random experiment performed in two steps

$$A = (\breve{A} \cdot \varepsilon_U) \cdot \varepsilon_R$$

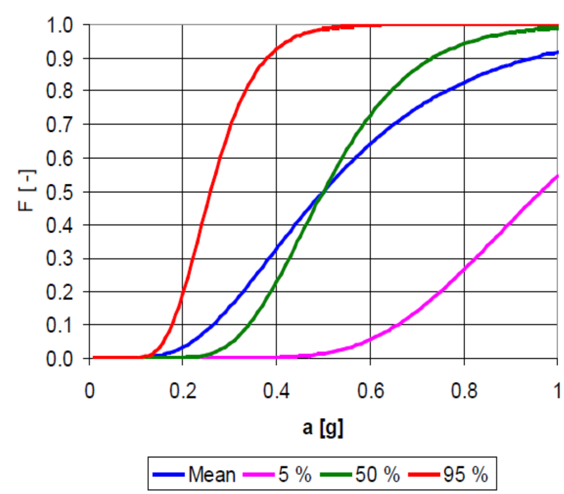
$\breve{A}$: Median value of the **population of scaling factors** that lead to onset of failure

$\varepsilon_R \sim LN(0, \beta_R)$ $\varepsilon_U \sim LN(0, \beta_U)$



➢ **Example of probability density functions (PDF)**

$\beta_R = 0.2, \beta_U = 0.3$



Randomness and uncertainty modeled as two distinct (subsequent!) random experiments:

$$\varepsilon_R\colon\ \Omega_1 \mapsto \mathbb{R}$$

$$\varepsilon_U\colon\ \Omega_2 \mapsto \mathbb{R}$$

State-of-the-art

- Separation of variables (Safety Factors)
- Numerical analyses
- Hybrid methods (Bayesian udpating)

Separation-of-Variables Method

$$\mathrm{Fr}(a) = \Phi\left(\frac{\ln\left(\frac{a}{\breve{A}}\right)}{\beta}\right)$$

- $a, A \rightarrow$ ground motion (peak ground acceleration)
- $\beta \rightarrow$ variability (logarithmic standard deviation)
- $\Phi \rightarrow$ cumulative standard normal distribution function

$$\breve{A} = \breve{F} \cdot A_{SSE}$$

Scaling (of SSE loads):
- Convenient because we can use results from deterministic calculations (SSE → safe shutdown earthquake → „design earthquake“); → **reason why this method has been used in 99% of the cases in NPP practice**
- Tolerated for rock sites
- Caution for soil sites, if spectral shape of UHS is different from SSE!

▶ Margin factor (cumulative, median)

$$\breve{F} = \breve{F}_{RS} \cdot \breve{F}_{RE} \cdot \breve{F}_{C}$$

▶ Capacity factor

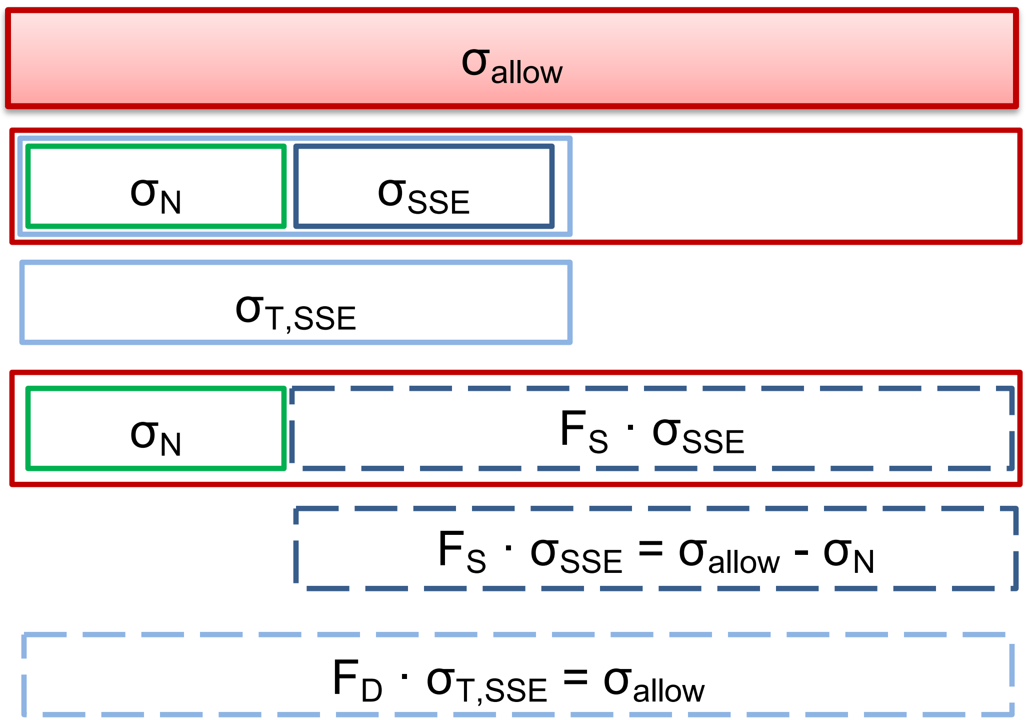
$$\breve{F}_{C} = \breve{F}_{S} \cdot \breve{F}_{\mu}$$

▶ Strength factor
- Failure mode dependent (ultimate stress, elastic limit, deformation, …)
- S → strength
- P → demand (e.g. stress); $P_{T,SSE}$ → total demand in case of SSE
- P_N → demand under normal conditions (no seismic loads)

$$\breve{F}_{S} = \frac{S - P_N}{P_{T,SSE} - P_N}$$

Separation-of-Variables Method

Why subtract non-seismic loads in strength factor?



F_S – Scaling seismic load only

F_D – Scaling all loads composing $\sigma_{T,SSE}$

F_S always larger than F_D because – besides scaling σ_{SSE} - we are also scaling σ_N .
(Red box will be full **EARLIER**.)

Separation-of-Variables Method
« Divide et impera »

EPRI (1994)
EPRI (2003)
EPRI (2009)

- **Assumption of a given design level IM_s**
- **The safety factor F represents the design margin**

$$\alpha = IM_s \cdot F$$

Decomposition of *F* for a structure subjected to seismic loading:

$$F = F_S \cdot F_\mu \cdot F_{SR}$$

Strength / Energy dissipation / Structural response

$$F_{SR} = F_{SA} \cdot F_{GMI} \cdot F_\delta \cdot F_M \cdot F_{MC} \cdot F_{EC} \cdot F_{SSI}$$

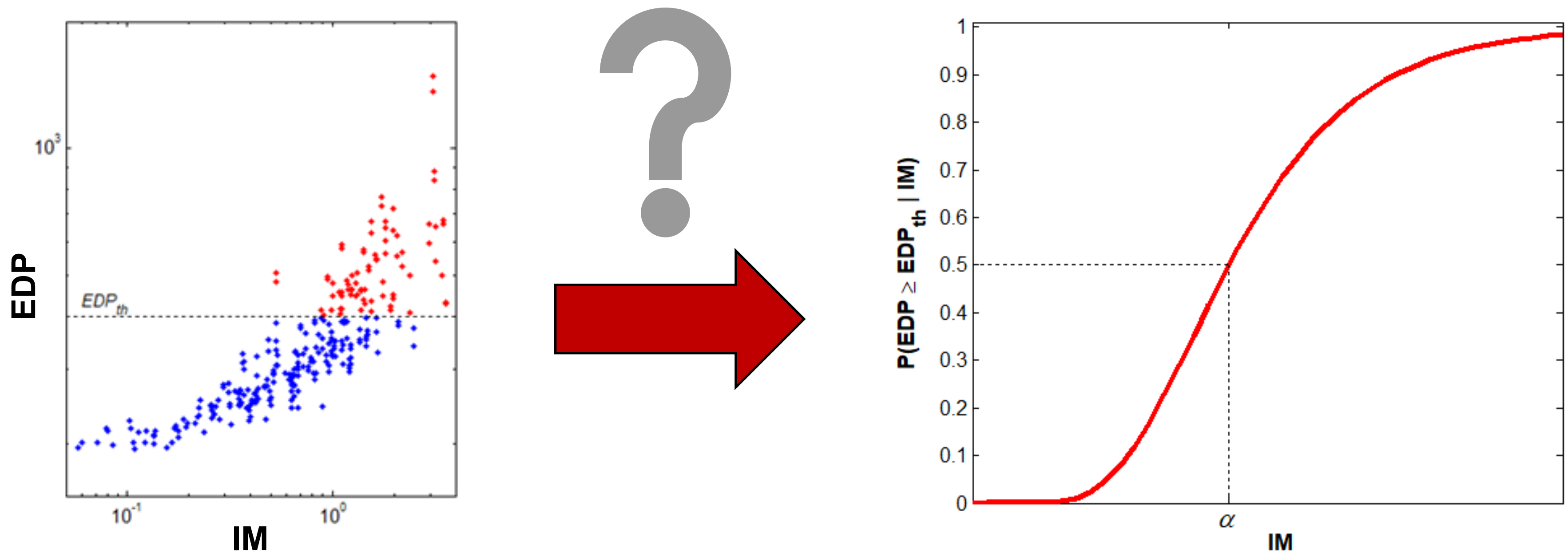
Decomposition of the dispersion term (quadratic combination):

$$\beta_U = \sqrt{\beta_S^2 + \beta_\mu^2 + \beta_{SA}^2 + \beta_{GMI}^2 + \beta_\delta^2 + \beta_M^2 + \beta_{MC}^2 + \beta_{EC}^2 + \beta_{SSI}^2}$$

Same formulation for β_R

Numerical Analyses

➢ Overview of the problem



Usually obtained from numerical simulations
(but also from experiments, observations from past events, etc.)

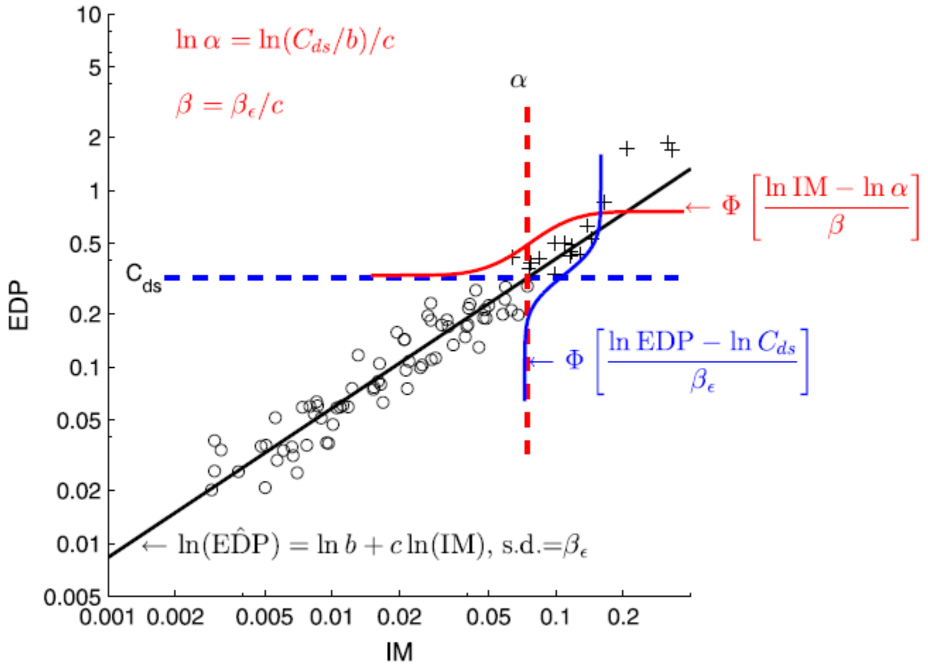
Numerical Analyses

➢ Least-Squares regression on the IM-EDP cloud

$$\ln \widehat{EDP} = \mathrm{a} + \mathrm{b}\ln IM + \varepsilon$$

Linear relation between the logarithms
➔ adequacy with the lognormal assumption

Error term: $\varepsilon \sim \mathcal{N}(0, \sigma)$



Identification of fragility parameters:

$$\begin{cases} \alpha = \exp\left(\dfrac{\ln EDP_{th} - a}{b}\right) \\ \beta = \dfrac{\sigma}{b} \end{cases}$$

Numerical Analyses

➢ Maximum Likelihood Estimation (MLE)

EDP ➔ binary damage variable *Y*:

$$\begin{cases} y_i = 1 & \text{if } edp_i \geq EDP_{th} \\ y_i = 0 & \text{if } edp_i < EDP_{th} \end{cases}$$

<u>Assumption:</u> binomial or Bernoulli distribution for *Y*

➔ Expression of the likelihood function of the fragility parameters *α* and *β*, given *N* data points:

$$L(\alpha,\beta) = \prod_{i=1}^{N} \left[P_f(im_i,\alpha,\beta)\right]^{y_i} \left[1 - P_f(im_i,\alpha,\beta)\right]^{1-y_i}$$

$$\{\hat{\alpha},\hat{\beta}\} = arg \max_{\alpha,\beta} L(\alpha,\beta)$$

Optimisation problem

Numerical Analyses

➢ Generalised Linear Method (GLM) regression

EDP ➔ binary damage variable *Y*:

$$\begin{cases} y_i = 1 & \text{if } edp_i \geq EDP_{th} \\ y_i = 0 & \text{if } edp_i < EDP_{th} \end{cases}$$

Fitting a linear combination of the input (based on *Y*):

$$g\left[P_f(im)\right] = c_1 + c_2 \ln im$$

Link function: $g = \Phi^{-1}$

(Probit model)

$$P_f(im) = \Phi(c_1 + c_2 \ln im)$$

$$\begin{cases} \alpha = \exp\left(-\dfrac{c_1}{c_2}\right) \\ \beta = \dfrac{1}{c_2} \end{cases}$$

By identification

<u>Other options:</u>

Logit, Loglog…

Wang et al. (2018)

Bayesian Updating

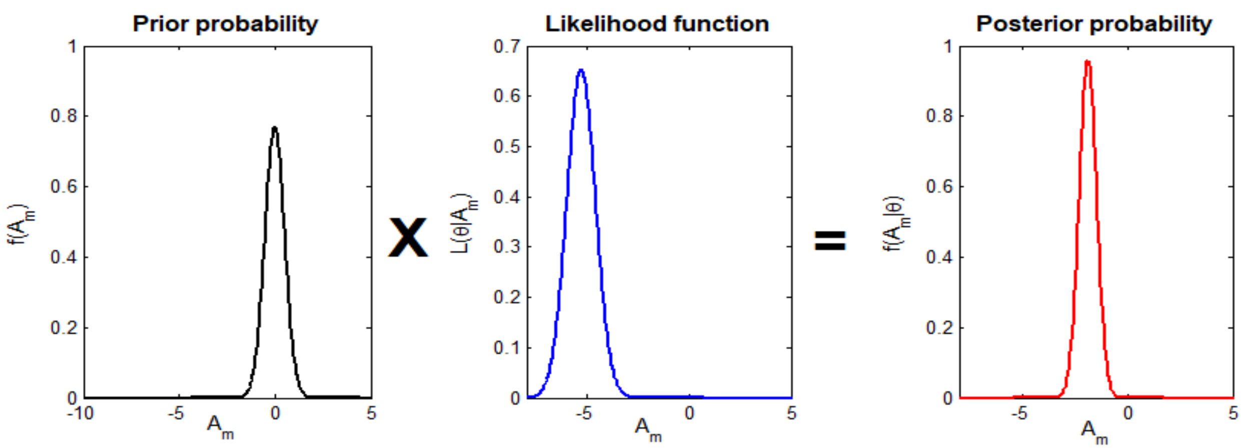
➢ Application of Bayes' rule

$$p^{post}(\theta|y) \propto p^{prior}(\theta).\,p(y|\theta)$$

- $p^{post}(\theta|y)$ → *Updated parameters, given evidence*
- $p^{prior}(\theta)$ → *A priori distribution of parameters*
- $p(y|\theta)$ → *Likelihood of observations*

θ = fragility parameters {α , β}

y = evidence (data gathered from experiments, observed damage)

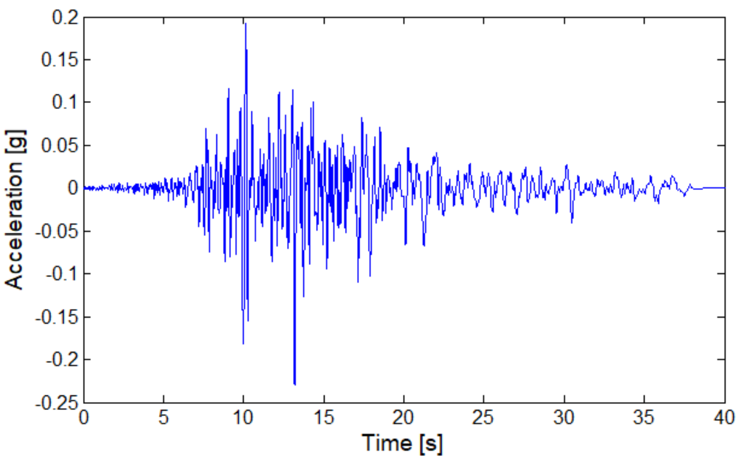


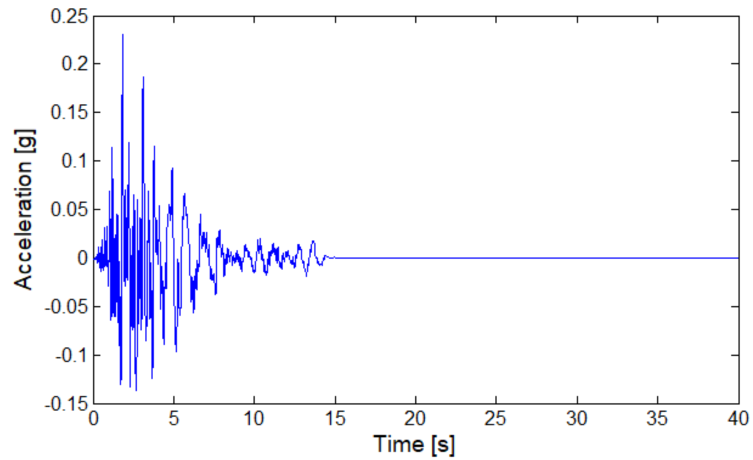
Summary of Methods

Method	Added value	Main limits	Example
Separation-of-Variables	- Reuse existing design calculations (high level of quality assurance!) -> cost-effective, good enough for vast majority of components;	- Assumes linearity of demand w.rt. IM (partial correction with inelastic energy absorption factor);	- EPRI TR-103959 (1994)
Regression "on a cloud"	- Simple and intuitive approach; - Stable fragility estimates may be obtained with a few data points;	- Constrained by the functional form of the IM-EDP relationship; - Constant standard-deviation over the IM range;	- Seismic fragility of an RC structure (Seyedi et al., 2010)
MLE / GLM regression	- Applicable to empirical fragility assessment (if only damage data are available); - Ability to treat complete damage/collapse cases (where EDP values are usually inaccurate); - Compatible with multivariate regression;	- Loss of information (i.e., the true values of the EDP are not used); - More data points are required to achieve stable fragility estimates;	- Seismic fragility of a masonry structure (Gehl et al., 2013); - Empirical tsunami fragility of buildings (De Risi et al., 2017);
Bayesian updating	- Compatible with expert-judgment approaches or Experimental results;	- Influence of the prior distribution on the final fragility estimates;	- Seismic fragility of switchgear cabinets (Wang et al., 2018)

Selection of Seismic IMs

➢ **Complexity of the ground-motion time histories**





Same PGA

➔ ***Frequency content?***

➔ ***Energy content?***

➔ ***Duration of strong motion?***

➔ ***Number of loading cycles?***

Record-to-record variability

Luco & Cornell (2007)

Padgett et al. (2008)

Selection of Seismic IMs

➢ Selection criteria

- ❑ *Efficiency*: ability of an IM to induce a low dispersion in the distribution of the structural response

$$\ln \widehat{EDP} = \mathrm{a} + \mathrm{b} \ln IM + \varepsilon$$

Low σ_ε ➔ High efficiency

- ❑ *Sufficiency*: ability of an IM to "carry" the characteristics of the earthquake that generated the ground motion

If $$P\left(EDP \middle| \ddot{x}_g\right) = P\left(EDP \middle| IM(\ddot{x}_g)\right)$$ **➔ IM is sufficient**

- ❑ *Practicality*: strength of the link between IM and EDP

$$\ln \widehat{EDP} = \mathrm{a} + \mathrm{b} \ln IM + \varepsilon$$

Large *b* ➔ High practicality

Luco & Cornell (2007)

Padgett et al. (2008)

Selection of Seismic IMs

➢ Selection criteria

❑ *Proficiency*: combination of practicality and efficiency

$$\ln \widehat{EDP} = \mathrm{a} + \mathrm{b} \ln IM + \varepsilon$$

Large b/σ_ε ratio ➔ High proficiency

❑ *Computability* or *Hazard compatibility*: ability to compute the selected IM accurately with current GMPEs

Computability grade	IM
1	PGA, PGV, AI, SA(T), RSD75, RSD95
2	PGD, ASI, SI, NED, JMA, CAV, NCy
3	ARMS, A95, SL75, SL95, SMA, SMV, DCy

1. IM associated with many well-constrained GMPEs (good estimation of the epistemic uncertainty)
2. IM associated with few well-constrained GMPEs (difficulty to judge the epistemic uncertainty)
3. IM associated with no reliable GMPEs

Selection of Seismic IMs

➢ Other methods to evaluate IMs / models

❑ Akaike Information Criteria (AIC):

$$AIC = 2k - 2\ln L$$

k **= number of parameters**

L **= likelihood function**

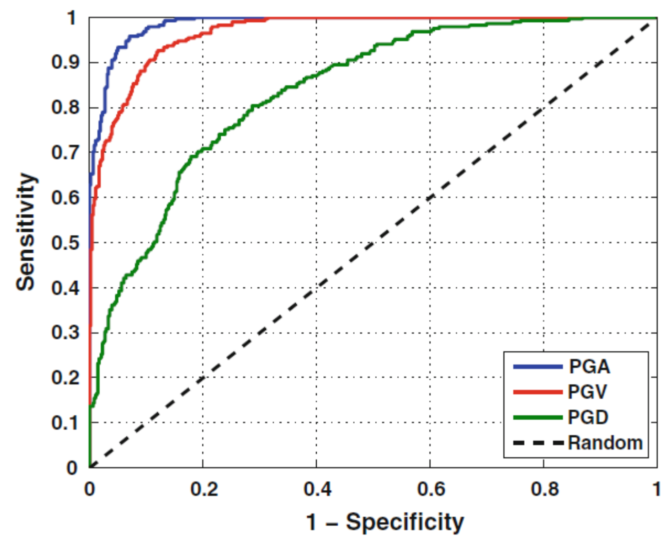
➔ Evaluates goodness-of-fit

❑ ROC (Receiver Operating Characteristics) analysis:

Construction of the ROC curve with increasing thresholds of damage probabilities:

$$\text{Sensitivity} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

$$\text{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}}$$



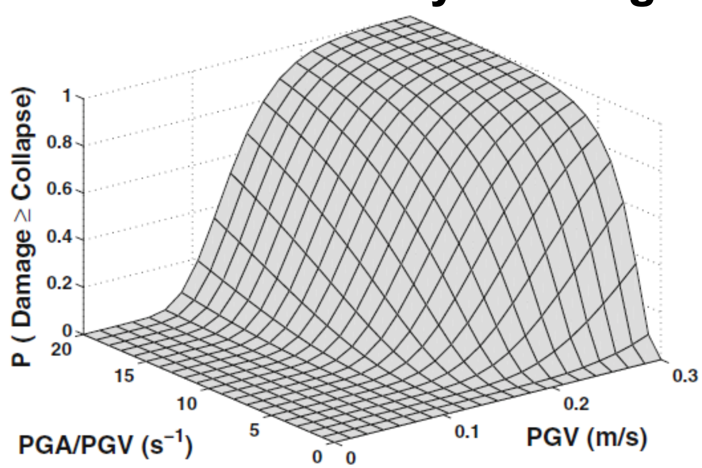
***Gehl et al.* (2013)**

Multi-Variate Fragility Functions

➢ Motivations

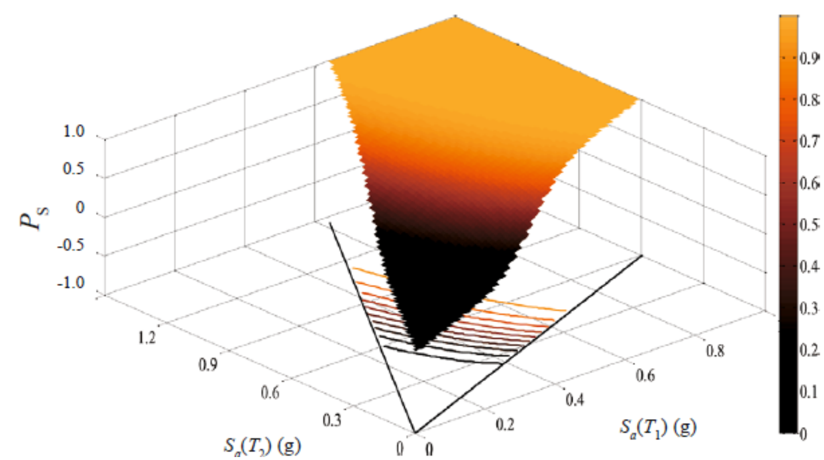
- ❑ Case of <u>seismic loading</u>: no single IM can perfectly fulfil the conditions of *efficiency* and *sufficiency*
- ❑ Other <u>hazard loadings</u> (e.g., flooding, wind): a combination of IMs is usually required (e.g., velocity, height)

Multi-variate seismic fragility of a masonry building



***Gehl et al.* (2013)**

Multi-variate seismic fragility of a bridge system



***Li et al.* (2014)**

Multi-Variate Fragility Functions

➢ Vector-IM fragility functions (or "fragility surfaces")

Functional form:

$$P_f(im_1, im_2) = P(DS \geq ds | IM_1 = im_1, IM_2 = im_2)$$
$$= \frac{1}{2}[1 + \mathrm{erf}(c_1 + c_2 \ln im_1 + c_3 \ln im_3)]$$

➔ ***Multi-variate GLM regression to estimate c_1, c_2, c_3***

Possibility of defining a composite IM:

$$im_V = im_1^{\frac{c_2}{c_2+c_3}} \cdot im_2^{\frac{c_3}{c_2+c_3}}$$

$$P_f(im_1, im_2) = P_f(im_V) = \Phi\left(\frac{\ln im_V - \ln \alpha_V}{\beta_V}\right)$$

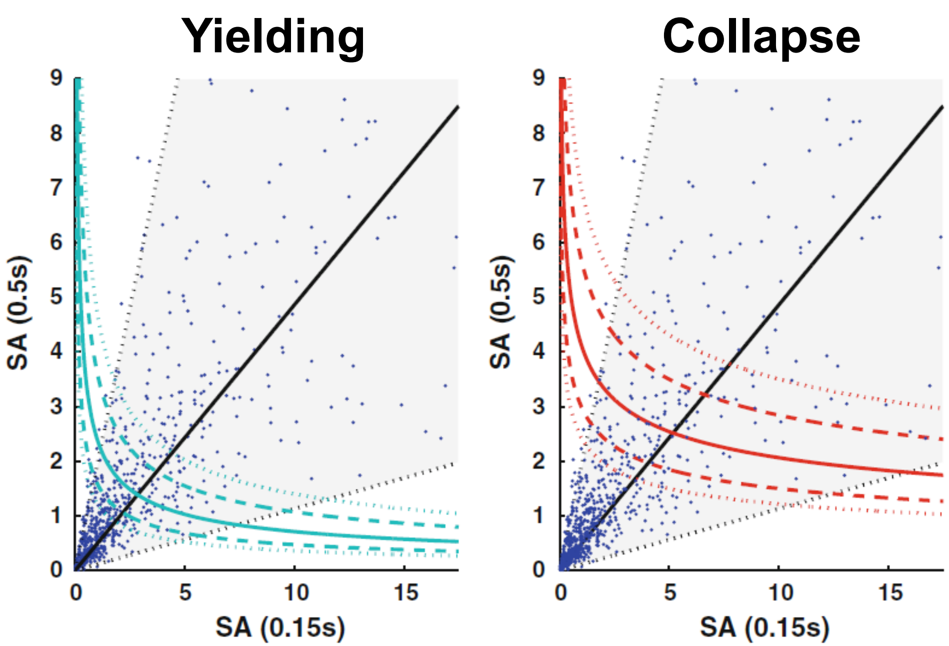
$$\begin{cases} \alpha_V = \exp\left(-\dfrac{c_1}{c_2 + c_3}\right) \\ \beta_V = \dfrac{1}{(c_2 + c_3)\sqrt{2}} \end{cases}$$

By identification

Multi-Variate Fragility Functions

- **Vector-IM fragility functions (or “fragility surfaces”)**
  - **Steeper “slope” of the vector-IM fragility functions (reduction of the record-to-record variability)**
  - **Need for a careful selection of IMs (issue of cross-correlation between IMs)**

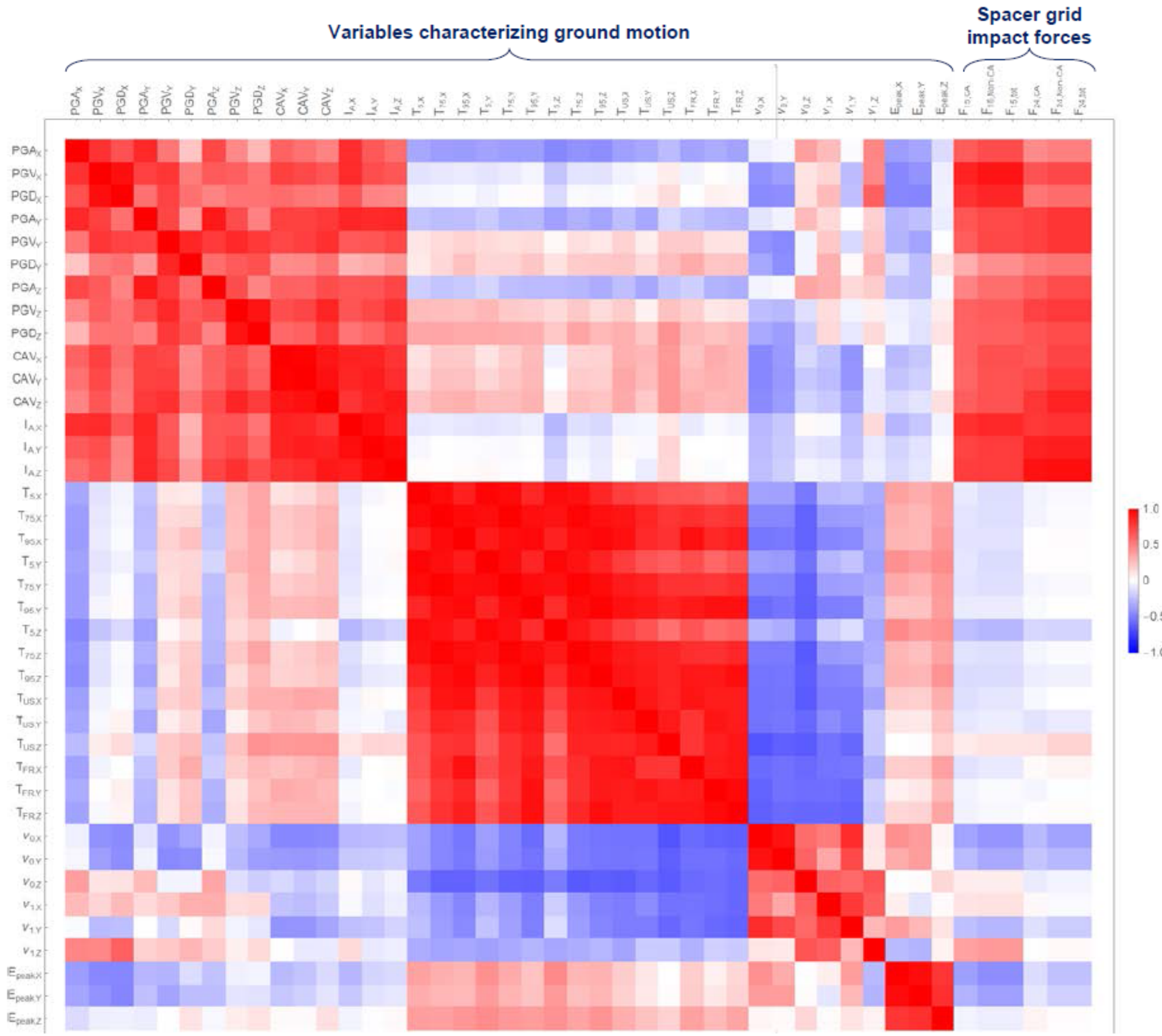
Example:



Gehl et al. **(2013)**

Multi-Variate Fragility Functions

Correlation map of various IM types (*Pellissetti et al.*, 2019)

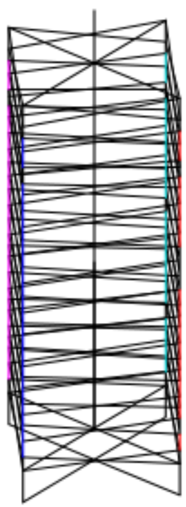


Application

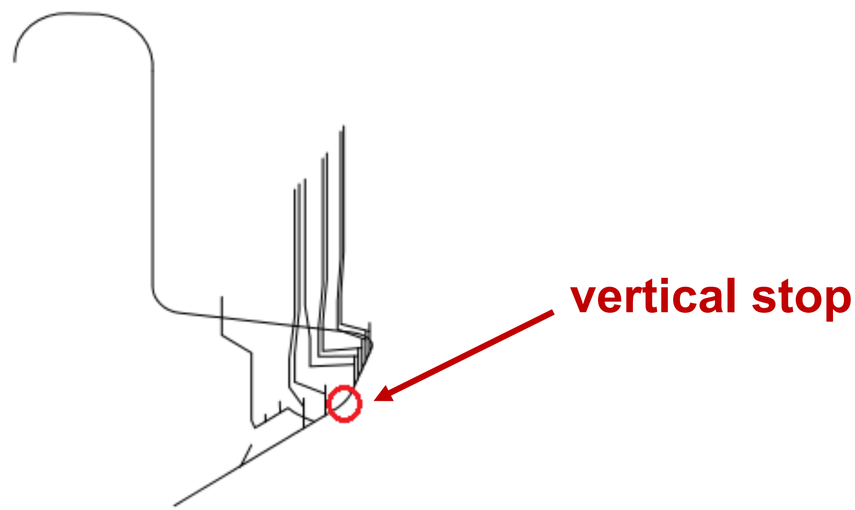
- **Model of a PWR main steam line**
  - Coupled model of a supporting structure and a steam line
  - CAST3M model from *Rahni et al.* (2017)
  - Derivation of fragility functions accounting for epistemic uncertainties and record-to-record variability

Mode #	Period [s]
1	0.38
2	0.38
3	0.15
4	0.14
5	0.14

containment building



steel steam line



Rahni *et al.* (2017)

Application

➢ Variation of structural and geometrical properties

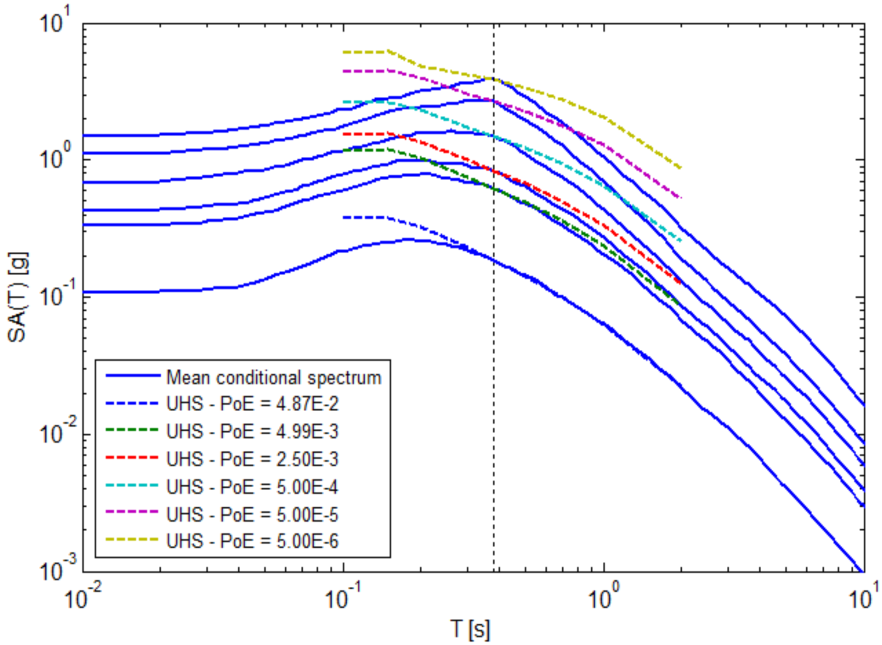
Variable	Description	Uniform distribution interval
E_{IC}	Young's Modulus – Inner containment	[27700 – 45556] MPa
ξ_{RPC}	Damping ratio – reinforced prestressed concrete	[4 – 6] %
ξ_{RC}	Damping ratio – reinforced concrete	[6 – 8] %
e_1	Pipe thickness – Segment #1	[29.8 – 38.3] mm
e_2	Pipe thickness – Segment #2	[33.3 – 42.8] mm
e_3	Pipe thickness – Segment #3	[34.1 – 43.9] mm
e_4	Pipe thickness – Segment #4	[33.3 – 42.8] mm
e_5	Pipe thickness – Segment #5	[53.4 – 68.6] mm
e_6	Pipe thickness – Segment #6	[34.1 – 43.9] mm
ξ_{SL}	Damping ratio – steam line	[1 – 4] %

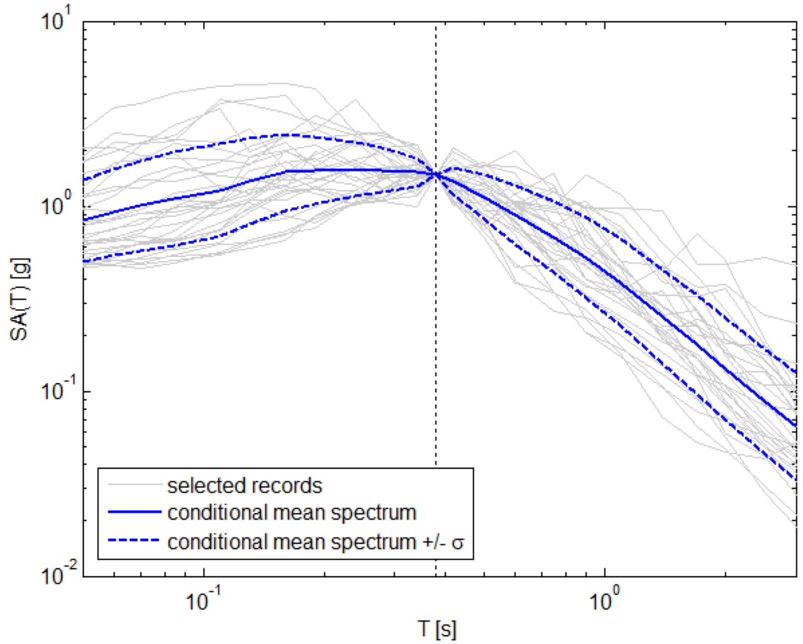
Generation of 360 model samples

Application

➢ Selection of ground-motion records

- ❑ Conditional spectrum approach (Lin et al., 2013)
- ❑ Conditioning period T_1 = 0.38s
- ❑ Selection for the PEER database (PEER, 2013)



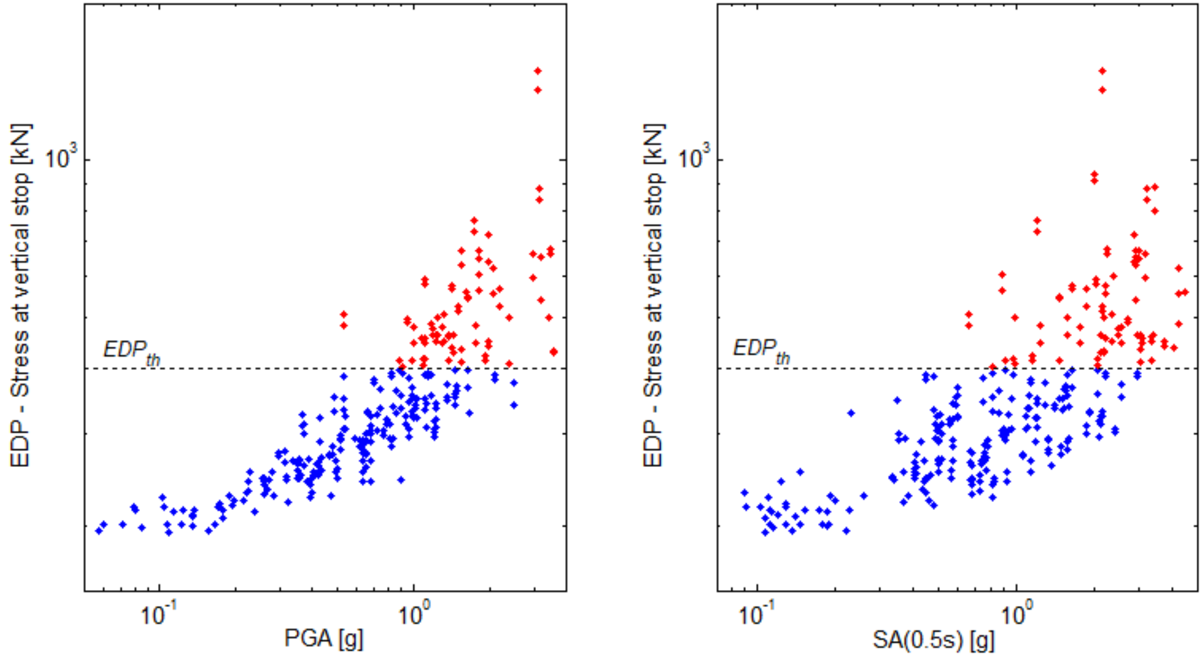


Gehl *et al.* (2019)

Application

➢ Non-linear time-history analyses

- ❑ 360 data points



- ❑ Failure criterion: load applied at the vertical stop = 400 kN

Gehl *et al.* (2019)

Application

➢ Selection of single IMs

IM	β	AIC	AUC
SA(0.14s)	0.5415	229.91	0.9166
SA(0.29s)	0.3898	175.82	0.9547
SA(0.50s)	0.5144	206.12	0.9363
PGA	0.4403	198.45	0.9399
PGV	0.4928	205.73	0.9381
PGD	1.2622	308.93	0.8469
AI	0.7674	182.13	0.9485
A95	0.4041	192.88	0.9389
SL75	0.9471	206.91	0.9325
SL95	0.7681	176.59	0.9508
SI	0.5293	213.94	0.9347
ASI	0.3775	176.23	0.9519
RSD75	-	-	-
RSD95	-	-	-
NCy	-	-	-
DCy	0.8123	191.58	0.9412
NED	1.4284	259.27	0.8968
CAV	0.6012	247.15	0.8951
ARMS	0.5728	240.45	0.9073

IM	Definition
PGA	Peak Ground Acceleration
PGV	Peak Ground Velocity
PGD	Peak Ground Displacement
AI	Arias Intensity
SA(T)	Spectral Acceleration at period T
A95	Level of acceleration that contains 95% of the Arias intensity
SL75 (95)	Slope of the Husid plot (cumulative AI over time) between 5% and 75% (and 95%) of the total AI
ARMS	Root-Mean-Square Acceleration: square-root of the integral of squared acceleration over time
ASI	Acceleration Spectral Intensity: integral of SA between two periods (here, 0:1s and 0:5s)
DCy	Cyclic Damage parameter: sum of the squared amplitude of all half-cycles, with the rainflow counting method
NCy	Number of effective Cycles: the same as DCy, except that the half-cycles' amplitudes are normalized by the amplitude of the largest half-cycles in the signal
RSD75 (95)	Relative Significant Duration: length of time interval between when AI first exceeds 5% of total value and when AI first exceeds 75% (and 95%) of total value
SI	Housner Spectral Intensity
NED	Normalised Energy Density: integral over time of the squared ground velocity
JMA	Japanese Meteorological Agency instrumental intensity
SMA (SMV)	Sustained Maximum Acceleration (and Velocity): the third highest value of the absolute maximum acceleration (and velocity)
CAV	Cumulative Absolute Velocity: integral over time of the absolute acceleration time-history

Application

➢ Selection of vector IMs

IM_1	IM_2	β_V	AIC	AUC
SA(0.14s)	*SA*(0.29s)	0.3724	173.71	0.9568
SA(0.14s)	*SI*	0.3464	167.19	0.9508
SA(0.29s)	*SA*(0.50s)	0.3834	173.74	0.9571
SA(0.29s)	*PGA*	0.3370	161.33	0.9424
SA(0.29s)	*PGV*	0.3718	171.22	0.9591
SA(0.29s)	*AI*	0.4687	171.69	0.9530
SA(0.29s)	*SI*	0.3659	167.43	0.9610
SA(0.29s)	*RSD95*	0.4371	174.11	0.9559
SA(0.50s)	*PGA*	0.3348	158.25	0.9439
PGA	*PGV*	0.3389	166.18	0.9532
PGA	*AI*	0.5027	170.79	0.9468
PGA	*SI*	0.3225	155.43	0.9339
PGA	*ASI*	0.3447	169.06	0.9416
PGV	*ASI*	0.3668	173.61	0.9526

➔ Slightly better performance than single IMs

➔ Some irrelevant parameters as single IMs now become useful (RSD)

➔ Interesting combinations:

[SA(0.29s) - PGA]

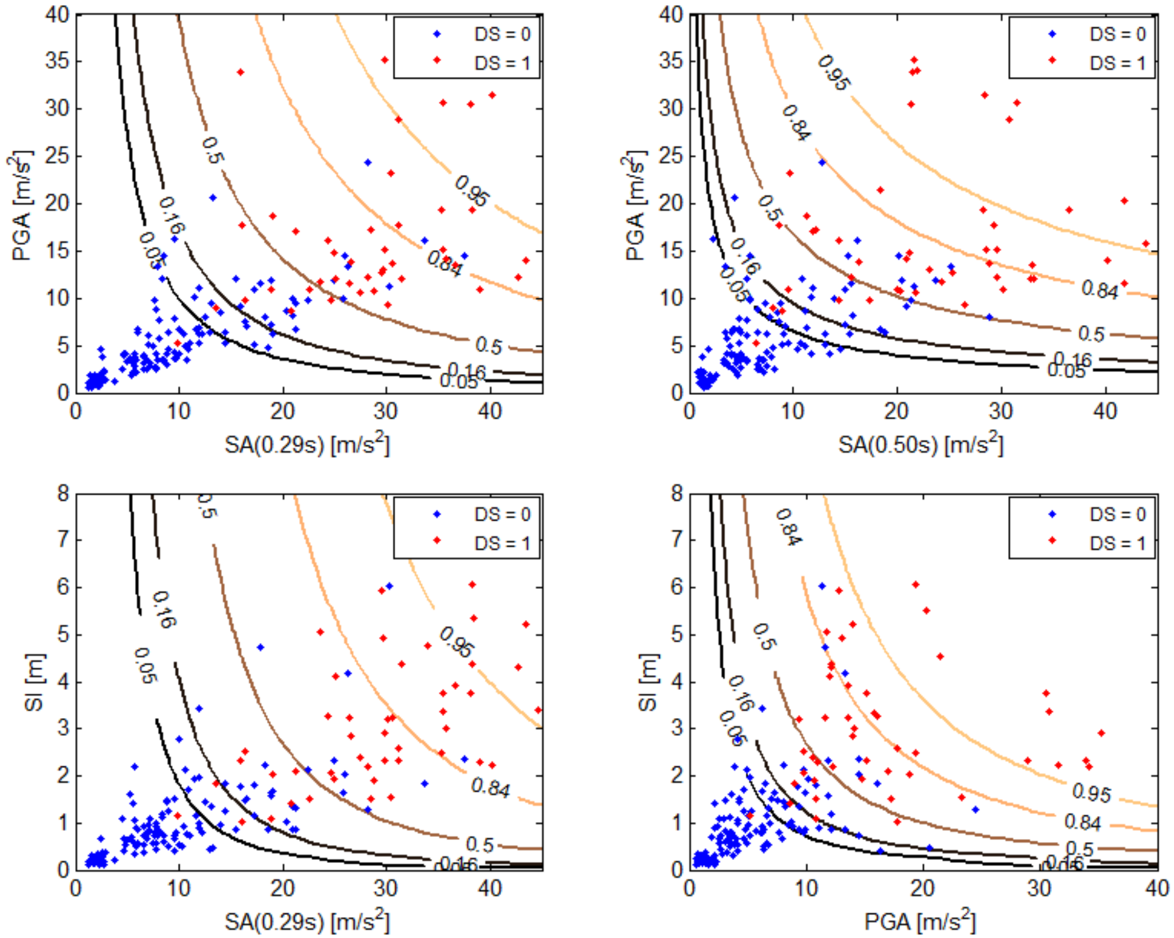
[SA(0.50s) - PGA]

[SA(0.29s) - SI]

[PGA - SI]

Application

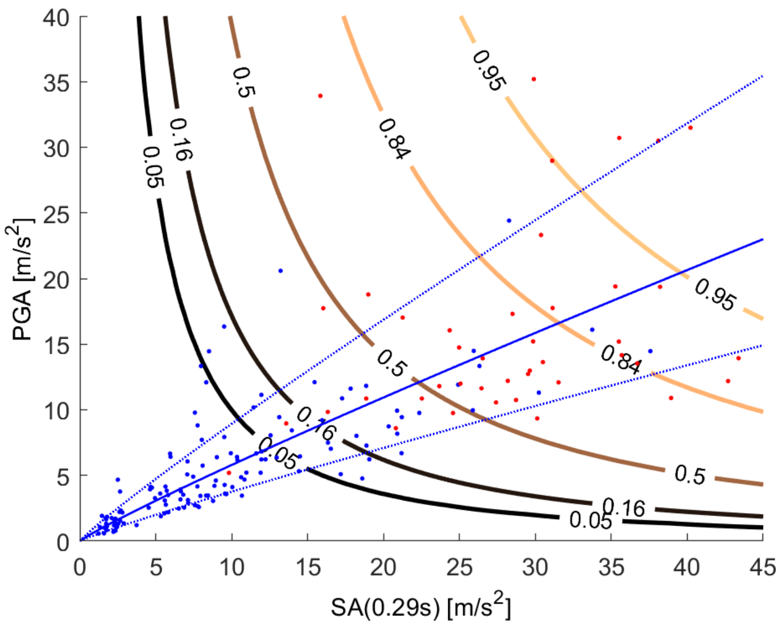
➢ Iso-probability lines of some fragility surfaces

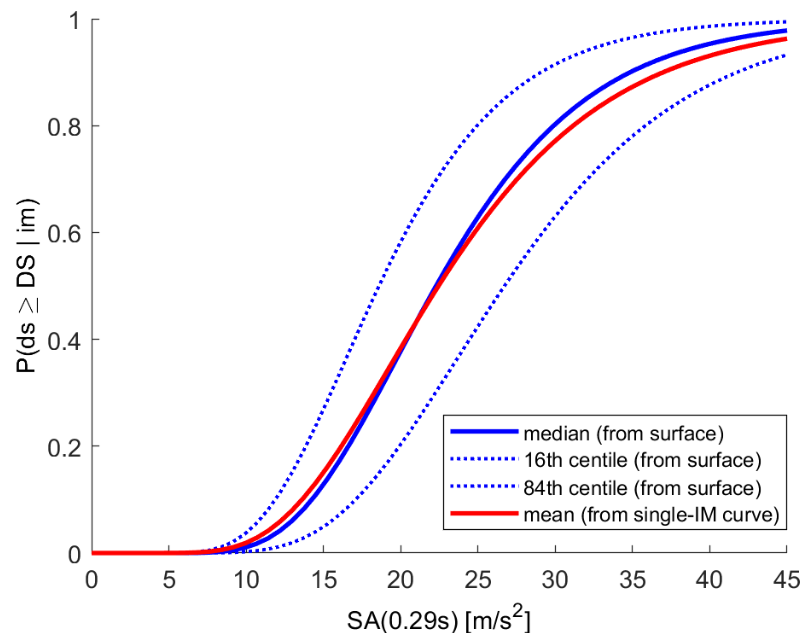


Application

➢ Uncertainty due to record-to-record variability

"Slices" of fragility surface ➔ **2-D fragility curves**





$\beta_C = 0.390$ { $\beta_R \approx 0.347$, $\beta_{U,1} \approx 0.174$ }

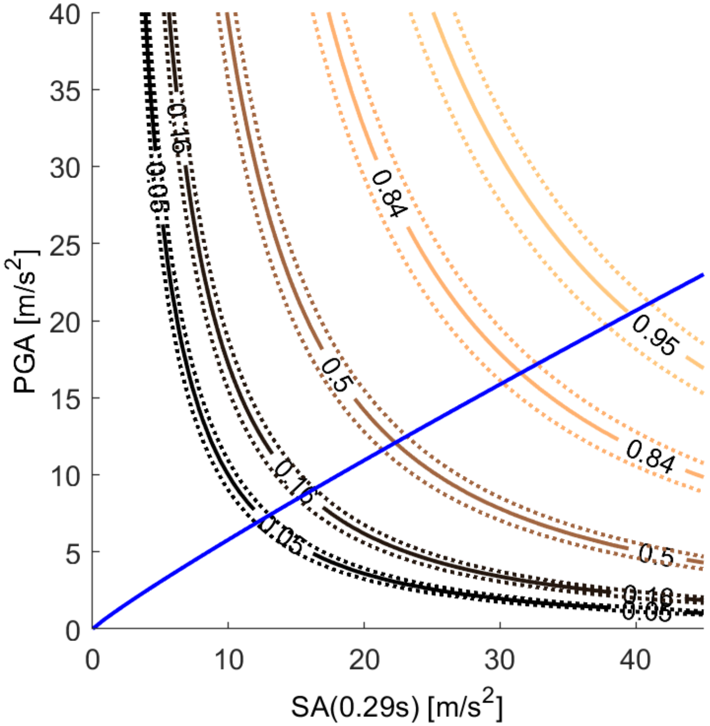
"Median" fragility curve with confidence bounds (vector-IM)

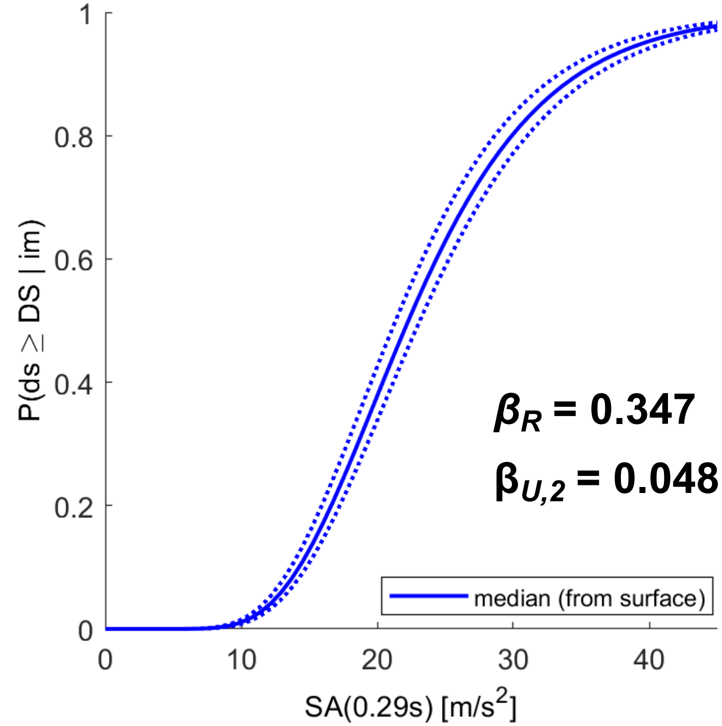
"Mean" fragility curve (single-IM)

Application

➢ Uncertainty due to statistical estimation of parameters

Bootstrap sampling to estimate the variation of the median parameter





➔ Very small contribution to the total uncertainty (enough data points?)

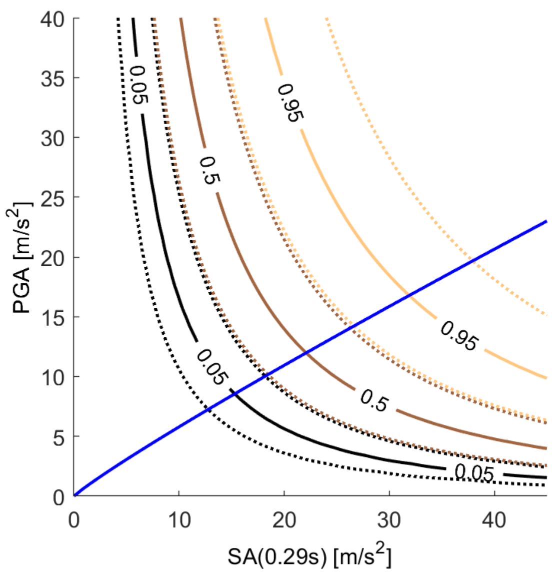
Application

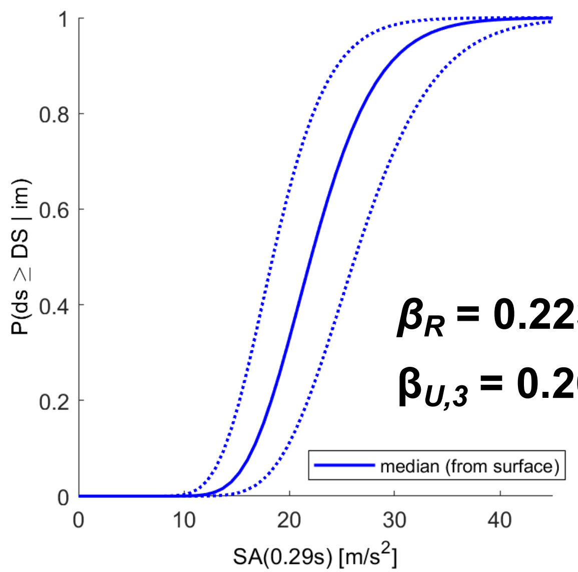
➢ Uncertainty due to mech. and geom. parameters

Multi-variate GLM regression, adding 3 thickness parameters (e_2, e_4, e_6)

Parameter	Regression coefficient	Std. Error	*p*-value (Wald statistic)
c_1 - Intercept	-22.008	4.030	4.73e-8
c_2 - SA(0.29s)	1.991	0.359	2.98e-8
c_3 - PGA	1.284	0.342	1.75e-4
c_4 - Thickness e_2	95.504	46.303	0.0392
c_5 - Thickness e_4	135.553	46.184	0.0033
c_6 - Thickness e_6	98.819	44.217	0.0254

$$g[P_f] = c_1 + c_2 \ln im_1 + c_3 \ln im_2 + c_4 e_2 + c_5 e_4 + c_6 e_6$$





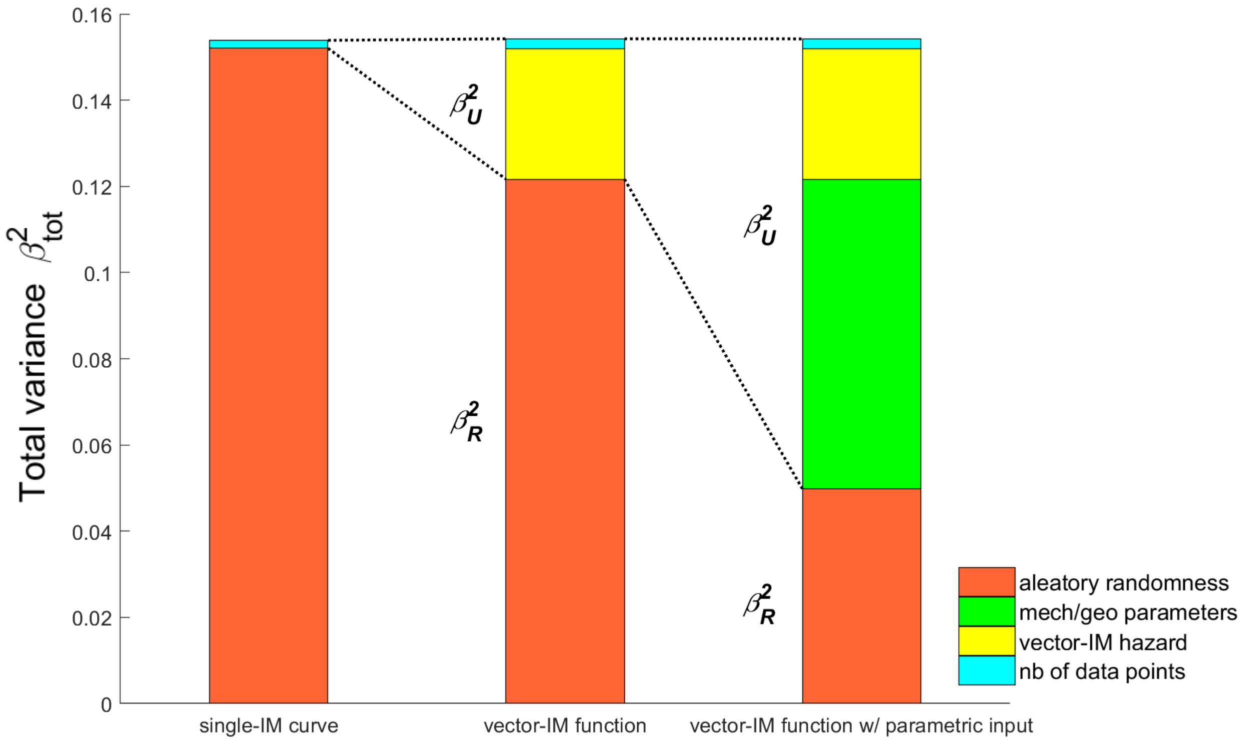
β_R = 0.223

$\beta_{U,3}$ = 0.268

➔ Large contribution of these modelling parameters

Application

➢ Decomposition of uncertainty terms



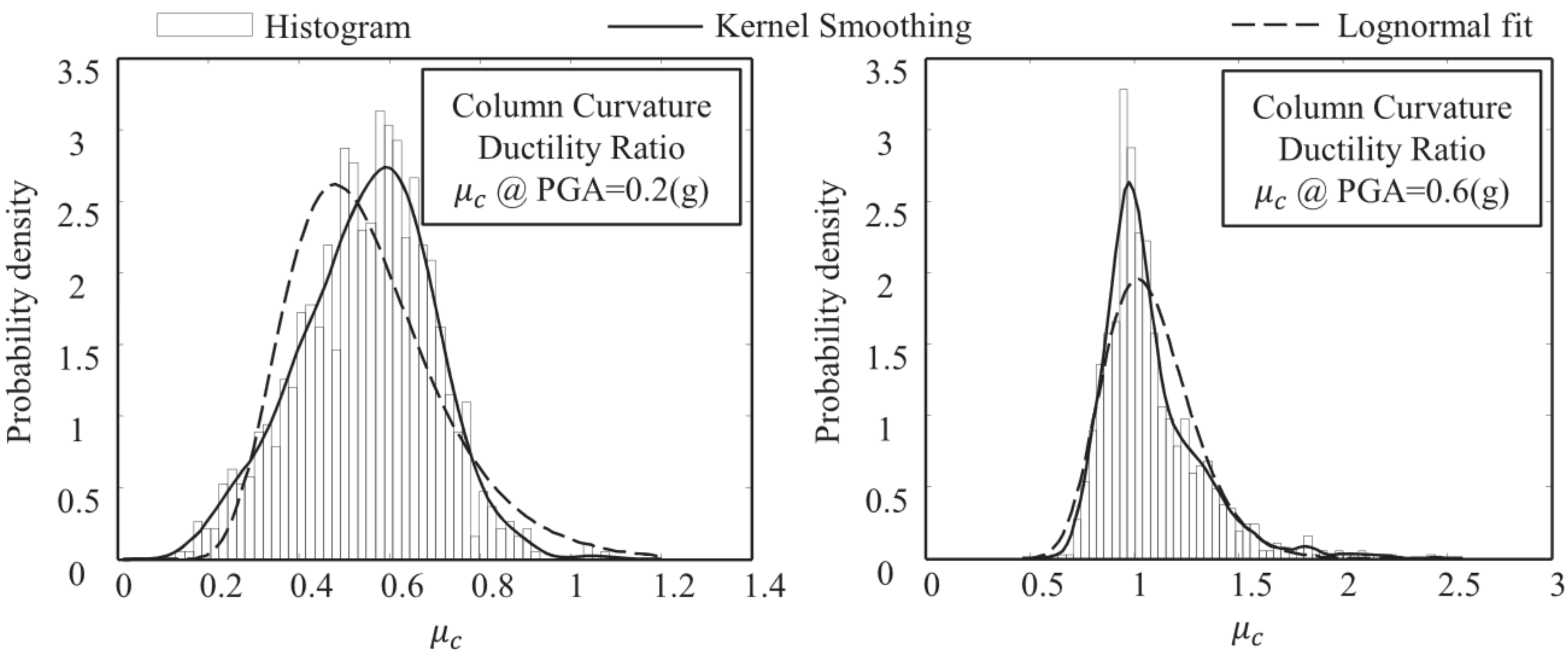
Link with HCLPF formulation:

$$SA(0.29\text{s})_{HCLPF} = \alpha_{SA}.\exp[-(\beta_R + \beta_U).\Phi^{-1}(0.95)]$$

➔ ***Reducing β_U leads to a larger HCLPF***

Validity of lognormal assumption?

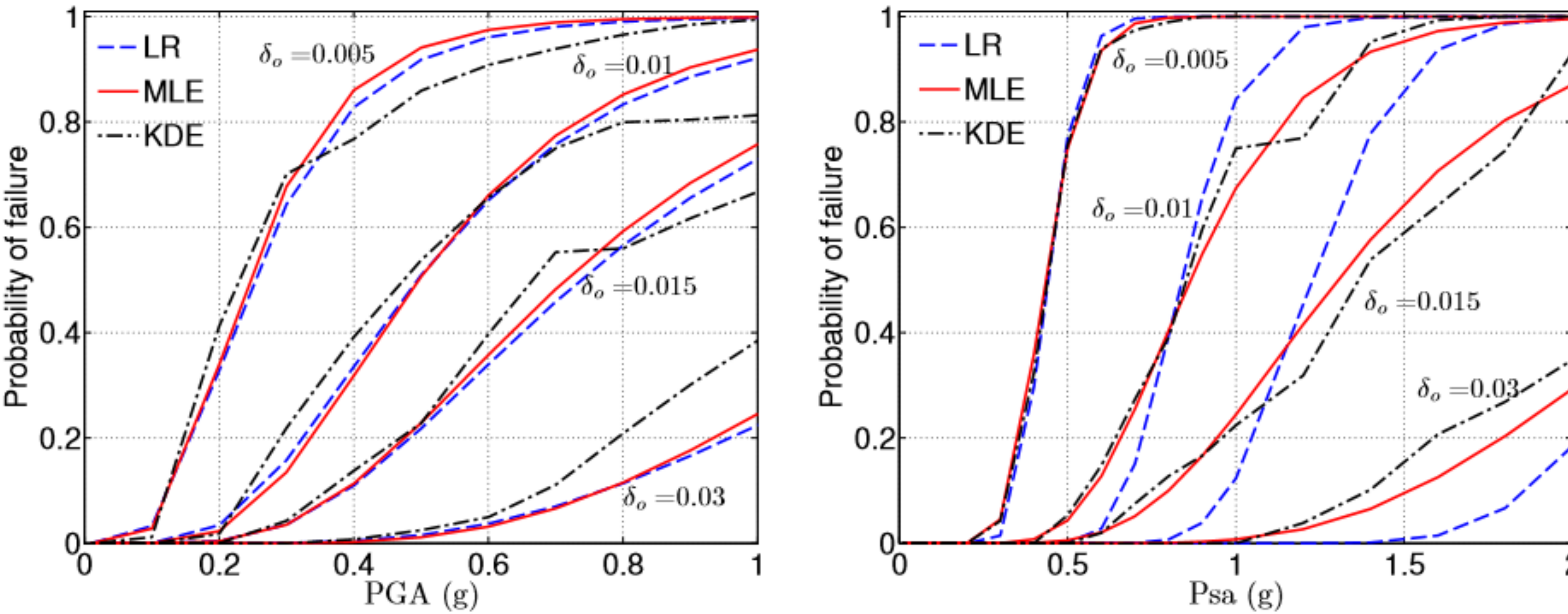
➢ **Distribution of the structural response of bridge columns**



Karamlou & Bocchini **(2015)**

Validity of lognormal assumption?

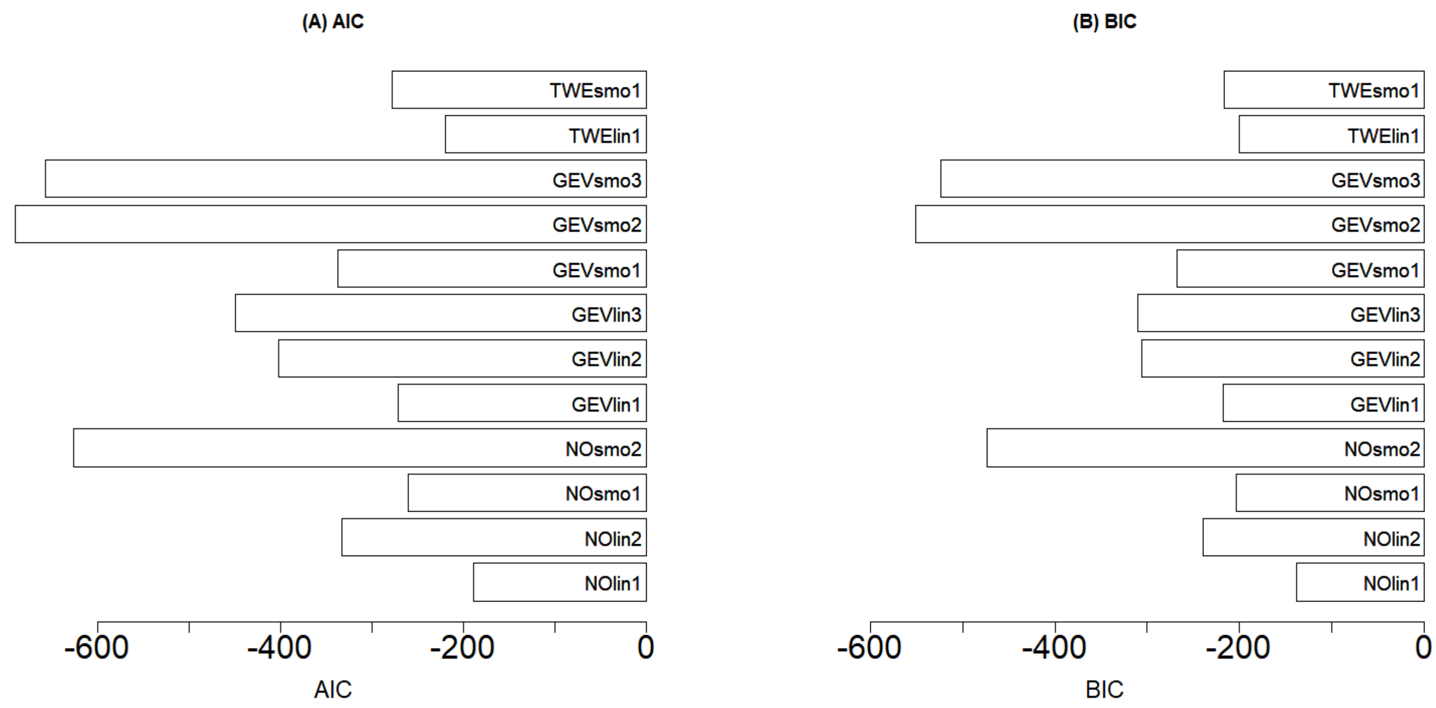
- **Seismic fragility functions of a steel frame structure**



Mai et al. **(2017)**

Validity of lognormal assumption?

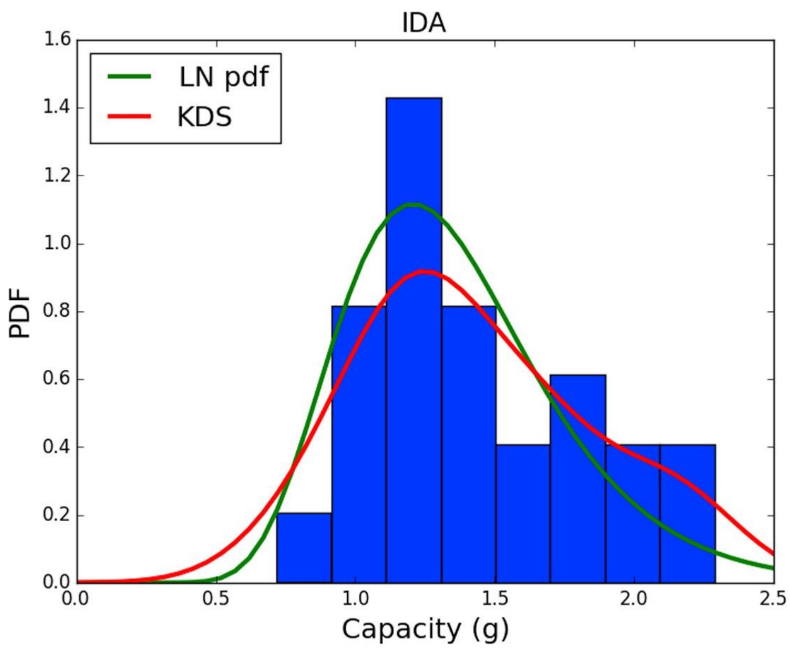
➢ **Comparison of fragility models for the NPP steam line**

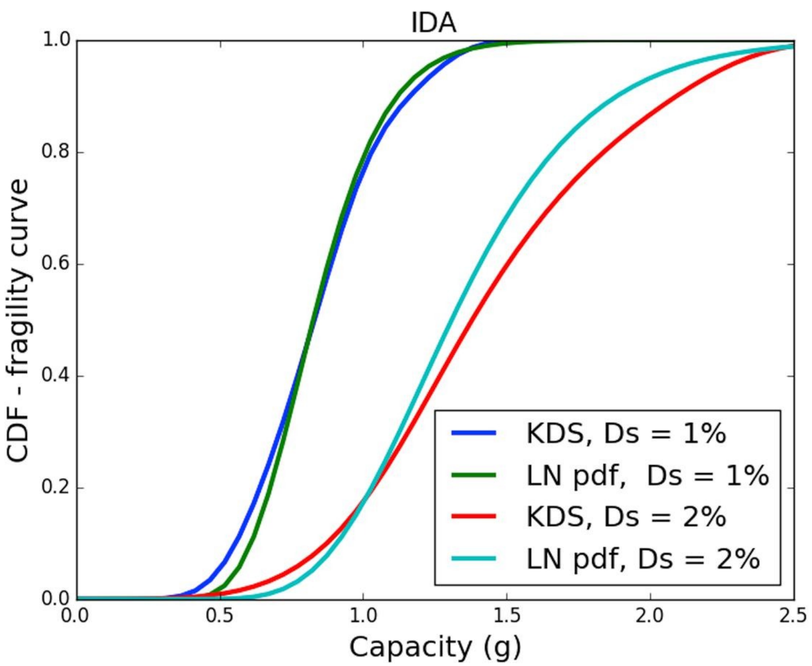


***Rohmer et al.* (2019)**

Validity of lognormal assumption?

➢ **Distribution of structural capacities (from IDA)**





***Zentner et al.* (2017)**

Conclusions

- In NPP practice, fragility based on a single IM (typically PGA) is the main-stream (and completely sufficient for most buildings / components)
- Traditionally, separation-of-variables has been used in the NPP fragility community, for convenience (and because it is often sufficient for most SSC)
- For specific SSC (limited margin, non-linear response) alternative "numerical" methods have been developed
- A single IM is typically not sufficient to predict the value of the relevant demand parameter of a structure or component (e.g. base shear, bolt stress, ...)
- Vector-valued fragility take into account more than one IM and can help to reduce the variability
- In order to be beneficial for NPP practice, i.e. applicable to seismic design and seismic risk analysis, it is necessary that the results from PSHA are also presented / post-processed in vector-valued form

Discussion

Any questions?

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