Dealing with Vague and Limited Information in Uncertainty Quantification

Michael Beer, Matteo Broggi Institute for Risk and Reliability

Ioannis Kougioumtzoglou Department of Civil Engineering and Engineering Mechanics

Edoardo Patelli Institute for Risk and Uncertainty 1Leibniz1212121314Hannover

COLUMBIA UNIVERSITY IN THE CITY OF NEW YORK



Thanks to: Liam Comerford, Marco de Angelis, Zhang Mingqiang, ... Uncertainty Quantification in Engineering

GENERAL SITUATION

Endeavor

numerical modeling – physical phenomena, structure, and environment
 prognosis – system behavior, hazards, safety, risk, robustness, economic and social impact, ...

» close to reality» numerically efficient

Deterministic methods



Uncertainty Quantification in Engineering

MULTI-DISCIPLINARY CHALLENGE

Major directions of development ... and combinations thereof







Michael Beer

JOINT TIME-FREQUENCY ANALYSIS

Civil infrastructure

- » seismic motions
- » ocean waves
- » winds
- » blast events
- » storms
- » hurricanes



Extreme Events

JOINT TIME-FREQUENCY ANALYSIS

Excitation

non-stationary

ocean waves,

blast events etc)

stochastic process

(earthquake, wind,



System

Response

non-stationary stochastic process

nonlinear and time-varying behavior due to severe dynamic excitation

• excitations with time-varying intensity & frequency content

joint time-frequency analysis

Wavelets

class of functions with compact support in both time and frequency domains used for the localization of a function in these domains Λ_{Λ}



Alfred Haar (1909)

Michael Beer

JOINT TIME-FREQUENCY ANALYSIS

Evolutionary Power Spectrum (EPS) estimation

- mathematical model for random process representation
 - » representation of random properties in correspondence with the EPS
 - » locally stationary wavelet process

$$f(t) = \sum_{j} \sum_{k} w_{j,k} \psi_{j,k}(t) \xi_{j,k}$$

- Generalized Harmonic Wavelets
 - » orthogonality & additional parameter
 - convenient frequency windowing
 - » flexible window size
 - » non-overlapping supports





distribution of "power" or "energy" of the underlying non-stationary stochastic process over different frequencies

basis for most engineering load models

JOINT TIME-FREQUENCY ANALYSIS

Incomplete data

- process records with gaps
 - » sensor failures
 - » data corruption
 - » power outages

» ...





Estimated spectrum of ANN reconstructions 25 records of length 512 - 50% missing data in random locations



Michael Beer

JOINT TIME-FREQUENCY ANALYSIS

Incomplete data

• Compressive sensing approach



Assume sparsity in a known basis

 Minimization of Σ_i|x_i| in Ax = y promotes sparse solutions
 Least squares L1 minimization



Stochastic process with 3 harmonics and white noise



Assume sparsity in harmonic basis to identify key frequencies



JOINT TIME-FREQUENCY ANALYSIS

Incomplete data

Compressive sensing approach
 » Harmonic basis construction

Wavelet basis (example)

Example for non-separable, nonstationary process: (50% randomly distributed missing data over 25 records using CS with a harmonic wavelet basis)





EXAMPLE: RELIABILITY ANALYSIS

Incomplete Earthquake Records



Simulated

EXAMPLE: RELIABILITY ANALYSIS

Incomplete Earthquake Records

• Scenario 1: data removed at random positions (10%, 20%, 30%, 40%)



EXAMPLE: RELIABILITY ANALYSIS

Incomplete Earthquake Records

• Scenario 2: data removed at 10 intervals located at random positions (10%, 20%, 30%, 40%)



Michael Beer

CHALLENGE



CLASSIFICATION AND MODELING

According to sources

- aleatory uncertainty
 - » irreducible uncertainty
 - » property of the system
 - » fluctuations / variability

stochastic characteristics

traditional probabilistic models

According to information content

- uncertainty
 - » probabilistic information
 - traditional and subjective probabilistic models

- epistemic uncertainty
 - » reducible uncertainty
 - » property of the analyst
 - » lack of knowledge or perception

collection of all problematic cases, inconsistency of information

no specific model

- imprecision
 - » non-probabilistic characteristics
 - set-theoretical models
- In view of the purpose of the analysis
- averaged results, value ranges, worst case, etc. ?

CLASSIFICATION AND MODELING

Simultaneous appearance of uncertainty and imprecision

- separate treatment of uncertainty and imprecision in one model
- generalized models combining probabilistics and set theory

concepts of imprecise probabilities

- » interval probabilities
- » sets of probabilities / p-box approach
- » random sets
- » fuzzy random variables / fuzzy probabilities
- » evidence theory / Dempster-Shafer theory

common basic feature:

set of plausible probabilistic models over a range of imprecision (set of models which agree with the observations)

bounds on probabilities for events of interest

IMPLEMENTING EPISTEMIC UNCERTAINTY

Subjective probabilities

• Bayesian update

 $f_{\Theta|X_{1},...,X_{n}}\left(\theta|X_{1},...,X_{n}\right) = \frac{\left[\prod_{i=1}^{n} f(x_{i}|\theta)\right] \cdot g_{\Theta}(\theta)}{\int \left[\prod_{i=1}^{n} f(x_{i}|\theta)\right] \cdot g_{\Theta}(\theta) d\theta}$

» approach result from "inside the epistemic uncertainty"

Imprecise probabilities

 set-theoretical models for indeterminacy / imprecision (imprecise data, vague conditions or copulas etc.)

 $F(x) = \left\{ \begin{bmatrix} F_{i}(x_{i}), F_{u}(x_{i}) \end{bmatrix} \forall x_{i} \right\} \quad \begin{array}{l} \text{e.g., set-valued parameters} \\ \text{in probabilistic models} \end{array}$

» approach result from "outside the epistemic uncertainty"

choice depending on available information and purpose of the analysis proaches not competing but complementary and can be combined

(e.g. set of priors, update with imprecise data)





FUZZY PROBABILITIES

Model

• fuzzy random variables $\widetilde{X}: \Omega \to F(\mathbb{R})$ (frequentist view)

fuzzy set of real-valued random variables $\tilde{X} = \{ (X_j, \mu(X_j)) | x_{ji} \in \tilde{x}_i \forall i \}$

 $\implies \text{fuzzy set of cdfs } \tilde{F}(x) = \left\{ \left(\mathsf{F}_{j}(x), \, \mu(\mathsf{F}_{j}(x)) \right) \ \left| \mathsf{X}_{ji} \in \tilde{\mathsf{X}}, \, \mu(\mathsf{F}_{j}(x)) = \mu(\mathsf{X}_{j}) \ \forall j \right\} \right\}$

Relationship to other concepts of imprecise probabilities

- evidence theory
 - » focal subsets represented by fuzzy sets
 - » frequentist view: probability of focal subsets induced by elementary events
- p-box approach
 - » fuzzy set of p-boxes $\tilde{F}(x) = \left\{ \left(F_{\alpha}(x), \mu(F_{\alpha}(x)) \right) | F_{\alpha}(x) = \left[F_{\alpha I}(x), F_{\alpha u}(x) \right], \right\}$

 $\mu\left(F_{\alpha}\left(x\right)\right) = \alpha \ \forall \alpha \in \left(0,1\right]\right\}$

Numerical processing

- stochastic techniques combined with interval / fuzzy analysis
 - » input: fuzzy set of plausible probabilistic models
 - » output: bounds on probabilities/probabilistic parameters for events/quantities of interest for several intensities of imprecision

FUZZY PROBABILITIES IN RELIABILITY ANALYSIS

Fuzzy parameters

Failure probability

- structural parameters
- probabilistic model parameters



coarse specifications of design parameters & probabilistic models
 attention to / exclude model options leading to large imprecision of P_f
 acceptable imprecision of parameters & probabilistic models

- indications to collect additional information
- definition of quality requirements robust design

μ(.) not important, but analysis with various intensities of imprecision 18/27

EXAMPLE: RELIABILITY ANALYSIS

Fixed jacket platform

- imprecision in the models for
 - » wave, drag and ice loads
 - » wind load
 - » corrosion
 - » joints of tubular members
 - » foundation
 - » possible damage

Collaboration with Profs. Quek Ser Tong Choo Yoo Sang

EXAMPLE: RELIABILITY ANALYSIS

Fixed jacket platform

- dimensions
 - » height: 142 m
 - » top: 27 X 54 m
 - » bottom: 56 X 70 m



- loads, environment
 - » T = 15° C, t = 5 a
 - » random: wave height, current, yield stress, and corrosion depth c(t,E)
 - » pdf / interval for imprecise parameters

Reliability analysis

• Monte Carlo simulation with importance sampling and response surface approximation



Collaboration with Profs. Quek Ser Tong Choo Yoo Sang

STOCHASTIC SAMPLING

Features

- generally applicable
 - » repeated analysis of deterministic model
 - » statistical evaluation of model response
- high numerical effort
 - implementations to increase numerical efficiency
 - » high performance computing
 - » efficient (variance reducing) sampling schemes
 - developments to further advance
 - » importance sampling
 - » subset sampling
 - » line sampling

in combination with subjective and imprecise probabilities



ADVANCED SAMPLING SCHEMES

Line sampling

- concept
 - \ast in the standard normal space approximate P_{f} through distances to the limit state at random locations
- practical implementation

 - » sample in S^{\perp}_{α} and find the distance $c^{(i)}$ to the limit state at the random points
 - \ast estimate P_f as average of the $p_f{^{(i)}}$ associated with the $c^{(i)}$

$$\widehat{P_{_f}} = \frac{1}{N_{_L}} \sum_{_{i=1}}^{N_{_L}} p_{_f}^{(i)} \qquad \widehat{P_{_f}} = \frac{1}{N_{_L}} \sum_{_{i=1}}^{N_{_L}} \varphi \left(-\overline{c}^{(i)} \right)$$

- » independent of
 - dimensionality and
 - \cdot magnitude of P_f



EXAMPLE: RELIABILITY ANALYSIS

Multi-storey building

- model
 - » 8,200 finite elements, 66,300 dof
 - » 244 random variables and 5 intervals (parameters of some rv)
- reliability analysis
 - » component failure
 - » line sampling
 - interval analysis
 with global optimization
 - » distributed computing

Analysis type	Sequential	Parallel
Direct Monte Carlo Simulation 10000 samples	> 6 days	~13 hours
Advanced MCS – Line Sampling 100 samples	1h 32 min	7.8 min



Method	Speed-up
Distributed computing	11.7
Advanced Simulation	~ 100
Advanced Simulation + Distributed computing	> 1000

HIGH-DIMENSIONAL PROBLEMS

Advanced Monte Carlo simulation with interval probabilities

- global optimization problem
 - $\frac{p_{f}}{p_{f}} = \inf_{\substack{x,p \ \Omega_{f}(x)}} h_{d}(\xi,p) d\Omega$ p distribution parameters $\xi - random variables$ x - intervals x - intervals

 $\Omega_{\rm f}$ depends on intervals x

• map intervals x to augmented probability space

 $\Omega \times X \to \Theta : \quad x \to \eta \in \mathbb{C}_{x} = \left\{ h_{n} \left(\eta ; \overline{\underline{\mu_{x}}}, \sigma_{x} \right) \middle| \underline{\overline{\mu_{x}}} = \underline{\overline{x}} \right\}$

 exploit topological properties of Θ for line sampling sampling direction –∇g

EXAMPLE: ROBUST RELIABILITY ASSESSMENT

Multi-storey building – component failure analysis

- structure
 - » 8,200 finite elements, 66,300 dof
- imprecise probabilistic input
 - » 488 fuzzy parameters for 244 fuzzy random variables





± 7.5 % tolerance range

SV $\#$	Prob. dist.	$\underline{\overline{p}} = p_c \ [1 - \epsilon, \ 1 + \epsilon]$		Description	Units
1	$N(\underline{\overline{\mu}}, \ \underline{\overline{\sigma}})$	$\mu_c = 0.1$	$\sigma_c = 0.01$	Columns' strength	GPa
2 - 193	$\operatorname{Unif}(\overline{\underline{a}}, \overline{\underline{b}})$	$a_c = 0.36$	$b_c = 0.44$	Sections' size	m
194 - 212	$LN(\overline{\underline{m}}, \ \overline{\underline{v}})$	$m_c = 35$	$v_c = 12.25$	Young's modulus	GPa
213 - 231	$LN(\overline{\underline{m}}, \ \underline{\overline{v}})$	$m_c = 2.5$	$v_c = 6.25 \ 10^{-2}$	Material's density	$\rm kg/dm^3$
232 - 244	$LN(\overline{\underline{m}}, \ \overline{\underline{v}})$	$m_c = 0.25$	$v_c = 6.25 \ 10^{-4}$	Poisson's ratio	-

EXAMPLE: ROBUST RELIABILITY ASSESSMENT

Multi-storey building – results

- advanced line sampling with pre-identified optimal points in $\boldsymbol{\Theta}$



Concepts in Uncertainty Quantification with Engineering Applications **RESUMÉ**

Major directions of development

- advanced stochastic modeling
- generalized models for vague and imprecise information

Monte Carlo simulation methods

combinations

➡ realistic models

→ efficient numerical analysis

UQ for industry-sized structures and systems
 improved design, performance and reliability