UQ and ML in Industry: Current Practices and Challenges in Industrial Applications for Low-Carbon Electricity Production

AISSAI Workshop on Artificial Intelligence and the Uncertainty Challenge in Fundamental Physics,
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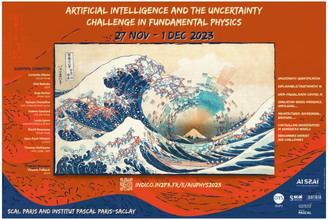
Foreword and acknowledgements

◆ Foreword

❏ This talk is given in the context of the AISSAI Workshop on Artificial Intelligence and the Uncertainty Challenge in Fundamental Physics (https://indico.in2p3.fr/event/30589/)



◆ Acknowledgements

❏ To the **organizers** of the workshop (CNRS AISSAI & CNRS IN2P3)

❏ To the **hosts** (SCAI / Sorbonne Université, Institut Pascal / Université Paris-Saclay)

❏ To all the **colleagues**, **Postdoc/PhD/Master students**, and **academic/industrial collaborators** who helped in a direct or indirect manner to create the content of these slides!

Doing Research and Development @ EDF R&D

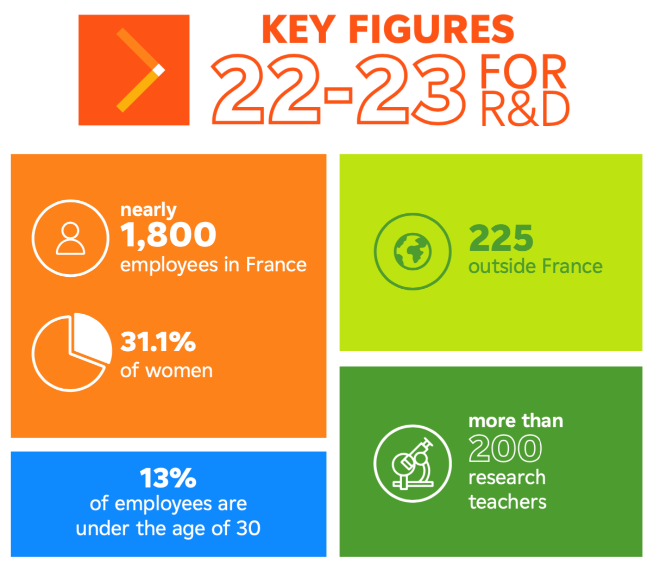


Figure 1: Key figures 2022-2023 for EDF R&D – part 1 (Source: EDF).

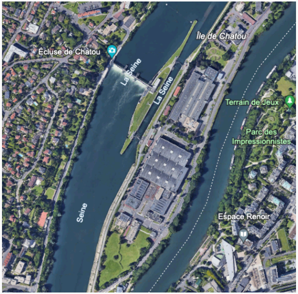
Doing Research and Development @ EDF R&D

Figure 2: Key figures 2022-2023 for EDF R&D – part 2 (Source: EDF).

Doing Research and Development @ EDF R&D

◆ Our (local) research environment

- Lab: EDF Lab Chatou (Western Paris, Island of Impressionists)
- Department: "Performance, Industrial Risk, Monitoring for Maintenance and Operating" (≈ 130 people)
- Group: "Asset Management, Uncertainty Quantification and Statistical Learning" (≈ 20 permanent researchers, ≈ 4 to 8 PhD/MSc students)



Introduction

Industrial context and motivations

◆ **Beyond the electricity bill...**

❑ EDF is a leading international energy supplier ➪ the ambition to produce zero carbon electricity in complete safety

❑ EDF operates a large panel of industrial assets

➥ nuclear power plants, dams and penstocks, wind turbines, etc.

❑ Electricity production facilities ➪ highly-safe complex industrial systems

➲ risk-sensitive industrial applications

➲ performance and safety are subject to several sources of uncertainty

Industrial context and motivations

◆ **A road trip through uncertainties!**

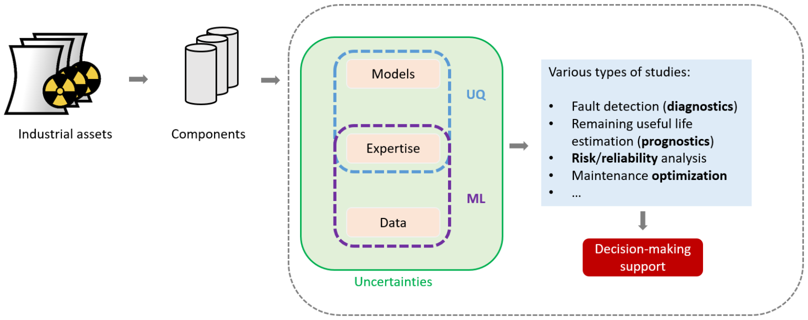


Figure 3: Dealing with uncertainties in an industrial process (©EDF).

☞ More about UQ in industrial practice: [DRDT08, DR12]

Industrial context and motivations

◆ **Why do we need UQ of computer models in our industry?**

- ❑ Computational modeling and simulation at EDF
  - ➤ Needed to model, design & predict the behavior of **complex engineering systems** (e.g., using digital twins)
  - ➤ Simulators ➪ substitute to / complementary to (costly or unfeasible) experiments (e.g., rare/extreme/undesired/risky configurations)
- ❑ Our simulators can be:
  - ➤ Static / time-dependent / spatiotemporal
  - ➤ Deterministic / stochastic
  - ➤ Low / high-fidelity $\Rightarrow$ cheap / costly-to-evaluate
  - ➤ Run on HPC / cannot!
  - ➤ Scalar-valued / vector-valued / mapping between functional inputs and functional outputs
  - ➤ Involve several codes (computational chain)
- ❑ ⚠ Boths inputs and models are **tainted with uncertainties**
- ❑ ⚠ Uncertainties play a key role at several stages (design, operation & maintenance, risk and safety assessment, production, ...)

- **Sources of uncertainty (⚠ from Engineers' point of view)**
  - ❑ Natural variability / randomness / stochasticity
    - ➤ intrinsic heterogeneity between individuals
    - ➤ w.r.t. time or/and space
      - ➥ soil mechanical properties, part manufacturing process, etc.
  - ❑ Modeling errors
    - ➤ modeling errors / model form inadequacy
      - ➥ numerical approximation, simplified equations, scenarios, etc.
    - ➤ input modeling uncertainties
      - ➥ statistical uncertainty, measurement uncertainty, etc.

Industrial context and motivations

◆ Aleatoric vs. epistemic: does it (really) matter?

- ❑ Etymology
  - ➤ Aleatory ➪ alea (Latin) $\equiv$ “rolling of a dice”
  - ➤ Epistemic ➪ $\epsilon\pi\iota\sigma\tau\eta\mu\eta$ (Greek) $\equiv$ “knowledge”
- ❑ Aleatory uncertainty
  - ➤ Can be seen as “irreducible” **within a specific context**
  - ➤ Seems to be rather “objective”
- ❑ Epistemic uncertainty
  - ➤ Can be seen as a lack-of-knowledge, thus potentially “reducible” **within a specific context**
  - ➤ Seems to be rather “subjective”
  - ➤ How? ➪ By adding more information (higher-order modeling, more data, more expert knowledge, etc.)
- ❑ Any consensus to decide whether sth is aleatoric or epistemic?
  - ➤ No scientific consensus! But... ☞ [DKD09]
  - ➤ ... a pragmatic approach is possible ➪ **it depends on the context!**
  - ➤ This distinction is debated not only in UQ, but also, recently, in ML ☞ [HW21]

Main objectives of the talk

- **The goals of this talk are ...**
  - ✔ To briefly introduce the UQ framework and a few links with ML
  - ✔ To provide an overview of a few motivating real-world applications
  - ✔ To give a highlight of related works we did in order to tackle them!
  - ✔ To make some advertisement for our tools and software!
- **This talk will not ...**
  - ✘ Present a rigorous lecture about UQ
  - ✘ Present use cases that can be easily reproduced

Table of contents

2. A few reminders about UQ and ML

Uncertainty Quantification in a nutshell

◆ **Verification, Validation & Uncertainty Quantification (VV&UQ)**

- ❑ Numerous scientific societies defined common engineering practices for VV&UQ (e.g., AIAA, ASME)

  ☞ https://www.asme.org/codes-standards/publications-information/verification-validation-uncertainty

- ❑ **Verification** ➪ to determine if the computational model fits the mathematical description
- ❑ **Validation** ➪ to determine if the model accurately represents the real world application
- ❑ **Uncertainty Quantification** ➪ to determine how variations in the numerical and physical parameters affect simulation outcomes

☞ To go further: [OR10]

◆ **Verification, Validation & Uncertainty Quantification**

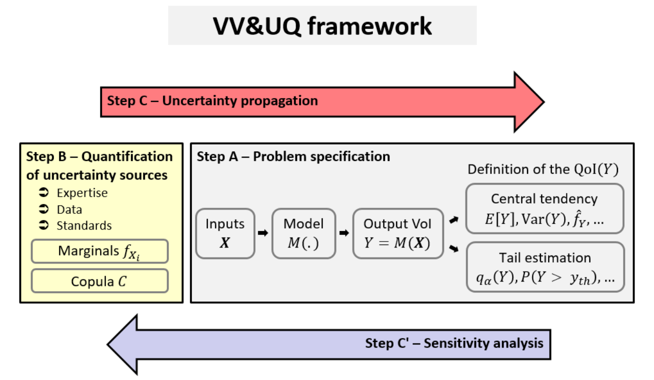


Figure 4: VV&UQ framework (©EDF).

☞ [Smi13, Sul15]

Uncertainty Quantification in a nutshell

◆ Step A – Problem specification

❏ Phenomenon of interest: physical, chemical phenomenon, etc.

❏ Computational modeling: $\mathcal{M} : \mathcal{X} \longrightarrow \mathcal{Y}$

❏ Input (physical) variables: $\mathbf{x} = (x_1, \ldots, x_d)$

❏ Output variable of interest (VoI): $y = \mathcal{M}(\mathbf{x})$

(+ a first hint in order to drive the next UQ steps)

❏ Quantity of Interest (QoI): QoI(Y)

- ➤ Central tendency analysis:

  ➥ QoI$(Y) := \mathbb{E}\left[Y\right]$ or QoI$(Y) := \mathrm{Var}\left(Y\right)$
- ➤ Tail (risk/reliability) analysis:

  ➥ QoI$(Y) := q_\alpha(Y)$ (e.g., $\alpha = 0.90/0.95/0.99$) or QoI$(Y) := \mathbb{P}\left(Y > y_{\mathrm{th}}\right)$

Uncertainty Quantification in a nutshell

◆ Step B – Quantification of uncertainty sources

- Assume you have:
  - Data (measurements, experiments, monitoring data, etc.)
  - Expertise (prior knowledge, bounds/constraints, distributions, feasible/unfeasible values, etc.)
  - Standards (recommendations, common engineering practice, etc.)
- Uncertain input (physical) variables: $\mathbf{X} = (X_1, \ldots, X_d) \sim P_{\mathbf{X}}$
  - If the variables are independent ➪ $P_{\mathbf{X}} := \prod_{j=1}^{d} P_{X_j}$
  - If they are dependent ➪ to learn d **marginal probability distributions** and the **copula** ☞ [Nel06, Leb13]
- How to construct this joint probability distribution?
  - Using parametric statistics (inference and tests)
  - Using nonparametric statistics (kernel smoothing, n.p. copula fitting)
  - Using Bayesian statistics
  - Using expert elicitation in order to derive bounds and supports
  - ...

Uncertainty Quantification in a nutshell

◆ Step C – Propagation of uncertainties

❑ Black-box model (with scalar output):

$$\mathcal{M} : \left| \begin{array}{ccc} \mathcal{X} \subseteq \mathbb{R}^d & \longrightarrow & \mathcal{Y} \subseteq \mathbb{R} \\ \mathbf{X} & \longmapsto & Y = \mathcal{M}(\mathbf{X}) \end{array} \right. \tag{1}$$

⚠ "Black-box" here ≡ nonintrusive w.r.t. the code $\mathcal{M}$

❑ Depending on the nature of the QoI(Y):

➤ **Central tendency estimation**

➥ analytical formulas, Monte Carlo simulations, ... ☞ [RK08]

➤ **Rare event estimation**

➥ approximation-based methods, variance reduction techniques (e.g., Quasi-Monte Carlo, Importance sampling), splitting techniques, etc. ☞ [MB15, DK22]

❑ ⚠ If $\mathcal{M}$ is costly-to-evaluate ➪ **surrogate models** $\widetilde{\mathcal{M}}$

➥ Gaussian processes, polynomial chaos expansions, support vector machines, ...

☞ [LGMS17, Bou18]

Uncertainty Quantification in a nutshell

◆ **Step C' – (Global) Sensitivity Analysis**

❑ SA settings "revisited" = Goal of the study ☞ [DGIP21]

1. Model exploration
2. Factor fixing ($\equiv$ Qualitative screening)
3. Factor priotization ($\equiv$ Quantitative ranking)
4. Robustness analysis (w.r.t. input distributions)

❑ A zoology of methods ➪ How to choose?

- ➤ Dependence structure in $P_{\mathbf{X}}$
- ➤ Linearity / nonlinearity of $\mathcal{M}$
- ➤ Input dimension and output dimension
- ➤ The nature of the QoI(Y) (target and conditional analyses)
- ➤ Computational constraints (limited simulation budget)
- ➤ (If you already have a surrogate model $\widetilde{\mathcal{M}}$ or not)
- ➤ ...

☞ [SRA+08, IL15, RJS+21, DGIP21]

Uncertainty Quantification in a nutshell

◆ Step C' – (Global) Sensitivity Analysis

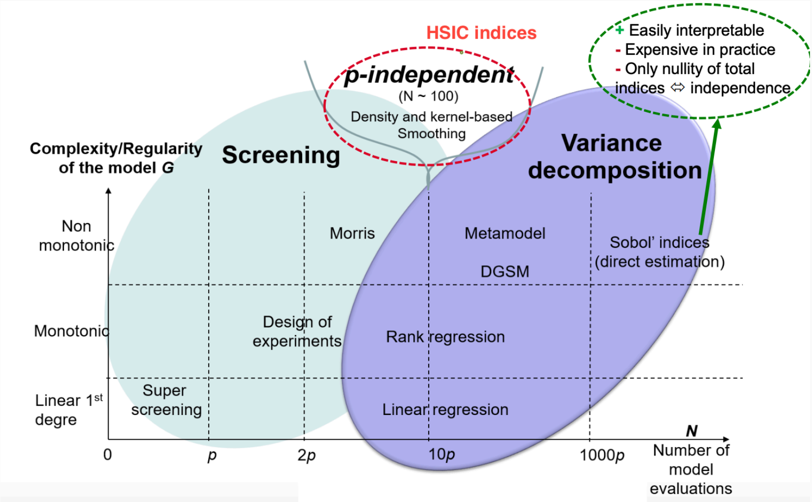


Figure 5: SA methods (Source: adapted from [IL15] by [Mar21]).

Supervised Machine Learning vs. UQ?

◆ **Supervised Machine Learning ...**
(not that much different from UQ)

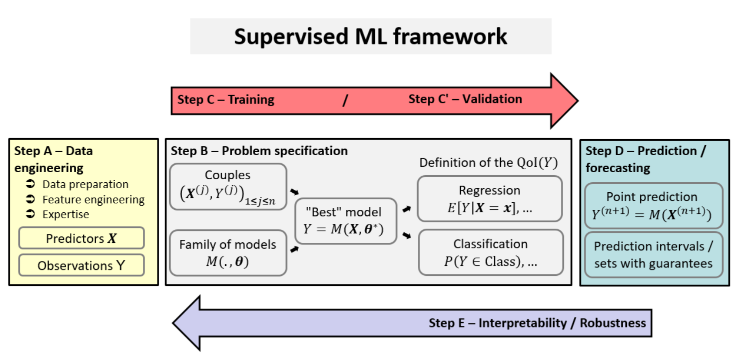


Figure 6: Supervised ML framework (©EDF).

Supervised Machine Learning vs. UQ?

◆ **A few recent links between supervised ML and UQ**

❑ Several analogies between VV&UQ and (supervised) ML:

- ➤ **Validation techniques** of statistical learning (surrogate / ML) models
  - ➪ using kernel-based methods such as **Kernel Herding** ☞ [FIM+22a]
- ➤ UQ for for robust prediction in ML
  - ➪ **Conformal Prediction** framework ☞ [JBB+23]
- ➤ **Global SA (given-data)** as a tool for ML Interpretability / Explainability
  - ➪ Regression-based importance measures ☞ [ICT22, CIC+nt]
  - ➪ Kernel-based indices (HSIC) ☞ [GBSS05, DV15]
  - ➪ Importance measures derived from Random Forests ☞ [B21]
- ➤ ...

3. Two challenging industrial use cases & related works

Two challenging industrial use cases & related works

- **Overview of the overview**
  - Two **use cases** (**UC**) are presented for the main electricity production assets
  - They arise from real-world engineering-related questions and challenges, focusing on **various goals**:
    - Safety analysis, risk and reliability assessment
    - Operating (statistical lifetime analysis, prognostics & health monitoring, maintenance optimization)
    - Robust design (under uncertainty) of new components and assets
    - Predictive analysis and new electricity usage
    - ...

UC#1 – Safety analysis of accidental transients

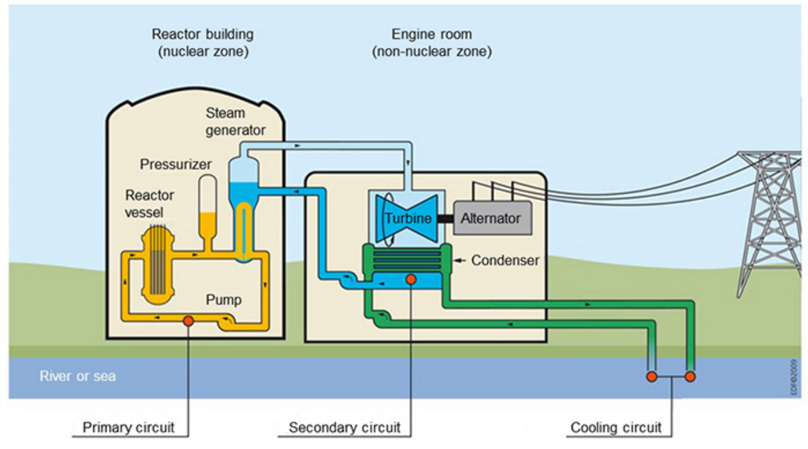


Figure 7: A typical French pressurized water reactor (source: IRSN).

☆ **The 3 safety barriers.**

➩ (#1) **cladding**, (#2) **primary circuit**, (#3) **reactor building**

UC#1 – Safety analysis of accidental transients

◆ Context of UC#1

- ❑ Scenario: Intermediate-Break Loss-Of-Coolant Accident (IBLOCA)
- ❑ Computer model: the CATHARE2 code (1 call ≈ 1 hour)

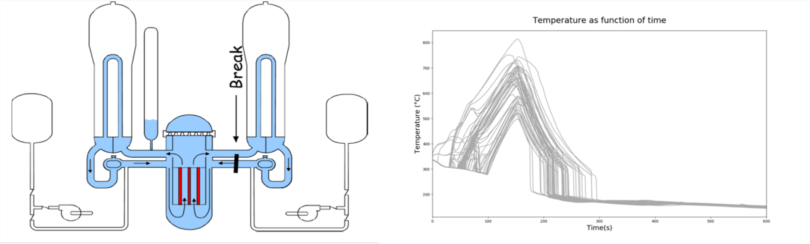


Figure 8: IBLOCA in a PWR (©CEA) / PCT trajectories from CATHARE2 (©EDF).

UC#1 – Safety analysis of accidental transients

◆ Context of UC#1

- ❑ Scenario: Intermediate-Break Loss-Of-Coolant Accident (IBLOCA)
- ❑ Computer model: the CATHARE2 code (1 call $\approx$ 1 hour)
- ❑ Inputs:
  - ➤ Type #1: Initial/boundary conditions ➪ probabilistic ($\mathcal{U}$, trunc. $\mathcal{N}$)
  - ➤ Type #2: Physical parameters ➪ probabilistic ($\mathcal{U}$, $\mathcal{LU}$, trunc. $\mathcal{N}$, $\mathcal{LN}$)
  - ➤ **Type #3: Scenario parameters ➪ not probabilistic (lower/upper bounds)**
- ❑ Output QoI: Second peak of cladding temperature (PCT) ➪ scalar QoI

☆ Main scientific/technical objectives.

- ❑ **(O1)** How to find the most penalizing values of Type #3 parameters?
- ❑ **(O2)** How to derive robustness indicators of risk-estimates w.r.t. input probabilistic modeling?
- ❑ **(O3)** How to detect functional outliers in transient simulations?

UC#1 – Safety analysis of accidental transients

◆ **Context of UC#1**

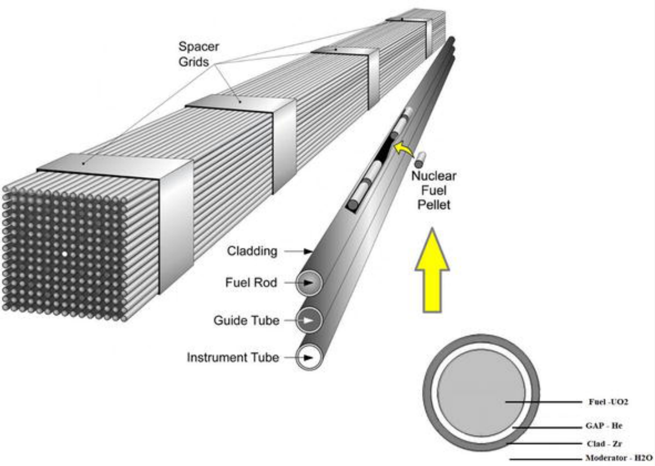


Figure 9: Nuclear fuel schematic (Source: US DoE and this website).

UC#1 – Safety analysis of accidental transients

$\hookrightarrow$ (O1) How to find the most penalizing values of Type #3 parameters?

⚠ Main challenges:

- ➤ $d \approx 100$ input variables, computational cost & nonlinearity
- ➤ Single input-output MC sample available ("**given-data**" framework)

☞ Proposed approach: ICSCREAM methodology [MIC22]

Main ingredients

- ❑ QoI ➪ $\widehat{q}_{0.90}(Y)$
- ❑ Use of **global** and **target SA** using the Hilbert-Schmidt Independence Criterion (HSIC) [DV15, MC21]
- ❑ Gaussian process (GP) regression
- ❑ Optimization under uncertainty
- ❑ Tracking nonmonotonic relationships

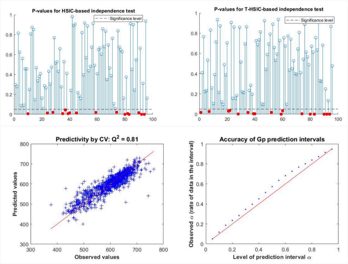


Figure 10: HSIC and GP regression.

↪ (O1) How to find the most penalizing values of Type #3 parameters?

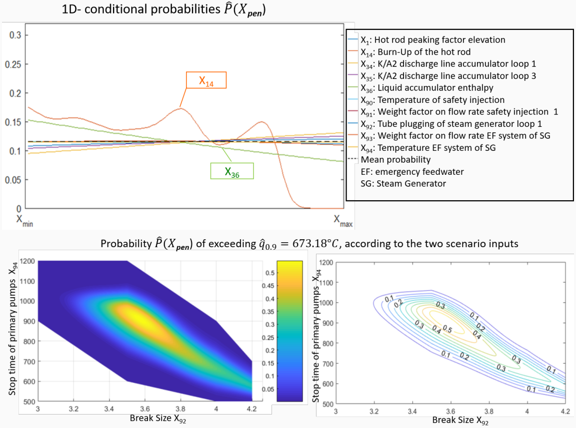


Figure 11: Illustration on 1D and 2D cases (Source: [MIC22]).

UC#1 – Safety analysis of accidental transients

↪ (O2) How to derive robustness indicators of risk-estimates w.r.t. input probabilistic modeling?

⚠ Main challenges: (same as before, plus...)

- QoI ➩ a **risk measure** (e.g., failure probability / high-order quantile / a super-quantile)
- Several sources of **epistemic uncertainties** (e.g., input distributions, model uncertainties)

☞ Proposed approaches:

(A.) Using **perturbation-based robustness measures** [Lem14, LSA+15, SID17, IVL22, GSSI22]

(B.) Using the **Optimal Uncertainty Quantification** (OUQ) framework [Ste20, SGKI20, SGK21]

(C.) Using the **Info-Gap** (IG) framework and **extra-probabilistic modeling** [Aje22, AAC+22, AAC+23]

UC#1 – Safety analysis of accidental transients

$\hookrightarrow$ **(O2) How to derive robustness indicators of risk-estimates w.r.t. input probabilistic modeling?**

(A.) Using perturbation-based robustness measures [Lem14, LSA$^+$15, SID17, IVL22, GSSI22]

Main ingredients

- Perturbed-law based (PLI) indices: $S_{j,\delta} = \dfrac{\text{QoI}(f_j^\delta) - \text{QoI}(f_j)}{\text{QoI}(f_j)}$
- MC and IS-based estimators for several QoIs with asymptotic guarantees
- Extensions to several QoIs and multivariate perturbations
- Generalization through **Information Geometry** and the Fisher-Rao distance (Optimal Fisher-based PLI)

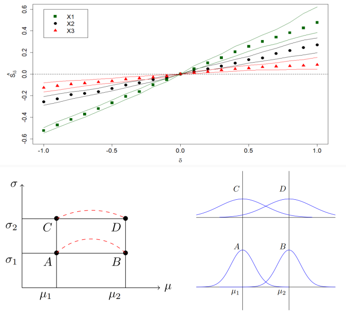


Figure 12: PLI and OF-PLI ([IVL22, GSSI22]).

UC#1 – Safety analysis of accidental transients

$\hookrightarrow$ (O2) How to derive robustness indicators of risk-estimates w.r.t. input probabilistic modeling?

(B.) Using the Optimal Uncertainty Quantification (OUQ) framework [Ste20, SGKI20, SGK21]

Main ingredients

- **OUQ principles** [OSS+13] ➪
  Evaluation of a maximum risk measure over a class of admissible measures

$$\inf_{\mu \in \mathcal{A}_\Delta} \mathbb{P}(G(\mathbf{X}) \leq h)$$

- Relies on the **Reduction Theorem** ➪ optimal solution of QoI optimization is a product of discrete measures
- Set of input measures reparameterized using **Canonical Moments** ➪ facilitates the optimization problem

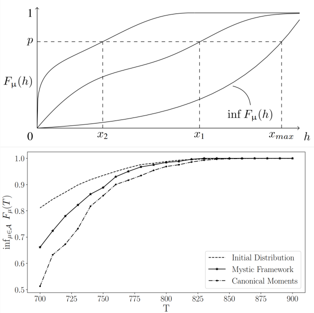


Figure 13: OUQ and canonical moments ([Ste20, SGKI20]).

UC#1 – Safety analysis of accidental transients

$\hookrightarrow$ **(O2) How to derive robustness indicators of risk-estimates w.r.t. input probabilistic modeling?**

(C.) Using the Info-Gap (IG) framework and extra-probabilistic modeling [Aje22, AAC$^+$22, AAC$^+$23]

Main ingredients

- **IG** [BH06] ➩ decision-theoretic framework under severe uncertainty
- Relies on the concepts of **horizon of uncertainty** and **robustness curve**
- Coupled with **random sets** [Mol17] ➩ generic framework for hybrid reliability assessment
- Proposition of efficient strategies based on advanced sampling and surrogate modeling

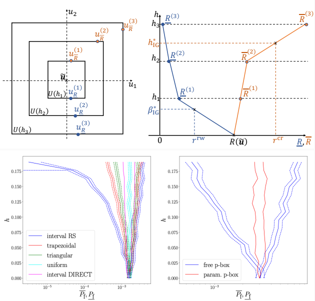


Figure 14: IG and robustness curves ([Aje22]).

UC#1 – Safety analysis of accidental transients

↪ **(O3) How to detect functional outliers in transient simulations?**

⚠ Main challenges: (same as before, plus...)

➤ No off-the-shelf method for expensive-to-evaluate computer simulations

☞ Proposed approach: **Functional Outlier Detection** (**FOD**) methodology adapted to strongly nonlinear nuclear transients [RDP21, RDPCI+21]

Main ingredients

- To measure the outlyingness both in the magnitude and shape senses [RDP21, RDPCI+21]
- Various features used (h-mode depth or DTW)
- Using HSIC indices in order to better interpret outliers

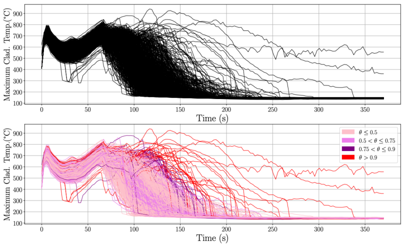


Figure 15: FOD on transients ([RDP21]).

UC#2 – Probabilistic fatigue assessment for offshore wind turbines

◆ Context of UC#2

- ❑ Scenario: reliability analysis of an offshore wind turbine (OWT)
- ❑ Computer model: complex computational chain

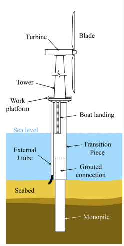


Figure 16: Monopile OWT diagram [FCMI23].

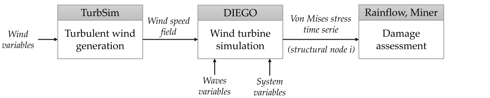


Figure 17: Computational chain [FCMI23].

UC#2 – Probabilistic fatigue assessment for offshore wind turbines

◆ Context of UC#2

- ❏ Scenario: reliability analysis of an offshore wind turbine (OWT)
- ❏ Computer model: complex computational chain (TurbSim - DIEGO - Damage)
- ❏ Inputs:
  - ➤ Environmental variables $\mathbf{X}$
- ❏ Output QoI: mean fatigue damage in the structure w.r.t. the environmental conditions

☆ Main scientific/technical objectives.

- ❏ **(O1)** How to build an input probabilistic model when inputs have a complex dependence structure?
- ❏ **(O2)** How to efficiently propagate uncertainties in a costly-to-evaluate computational chain?

UC#2 – Probabilistic fatigue assessment for offshore wind turbines

↪ **(O1) & (O2) Learning complex dependence structure + Efficient uncertainty propagation?**

⚠ Main challenges:

- ➤ Large dataset of environmental conditions (given-data)
- ➤ Complex dependence structures among inputs

☞ Proposed approach: Using the **empirical Bernstein copula** and **Kernel Herding** [FCMI23]

Main ingredients

- ❏ Nonparametric copula fitting ➪ **empirical Bernstein copula** [Las22, FCMI23]
- ❏ Use of Kernel Herding [CWS10] ➪ subsampling and efficient propagation of uncertainties [FIM+22b, FCMI23]

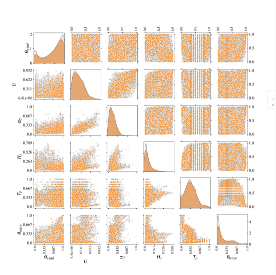
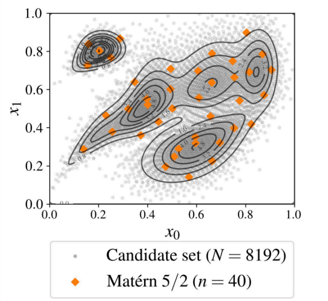


Figure 18: Copulogram.

UC#2 – Probabilistic fatigue assessment for offshore wind turbines

↪ (O1) & (O2) Learning complex dependence structure + Efficient uncertainty propagation?



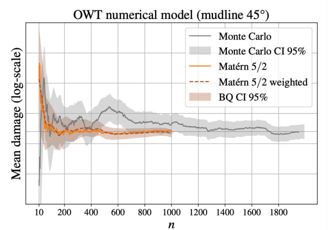


Figure 19: Kernel Herding applied to a 2D and OWT cases (Source: [FCMI23]).

4. Open source tools and software for UQ

OpenTURNS: an open-source library for UQ

❑ OpenTURNS in a few words:

- An **Open** source initiative for the **T**reatment of **U**ncertainties, **R**isks'**N** **S**tatistics ☞ [BDIP17]
- Started in 2004...
- Last version: 1.21 (summer 2023, 2 releases / year)
- Developed (LGPL License) by
  Airbus - EDF - IMACS - ONERA - Phimeca
- core & API
  ➪ **conda/pip install openturns**

❑ More information?

- Website: https://openturns.github.io/www/
- Github: https://github.com/openturns/openturns
- Discourse: https://openturns.discourse.group/
- Gitter: chatting for short questions and problems
- Stack Overflow: tag 'openturns'
- OT modules: several specific modules (packages) on this page

OpenTURNS: an open-source library for UQ

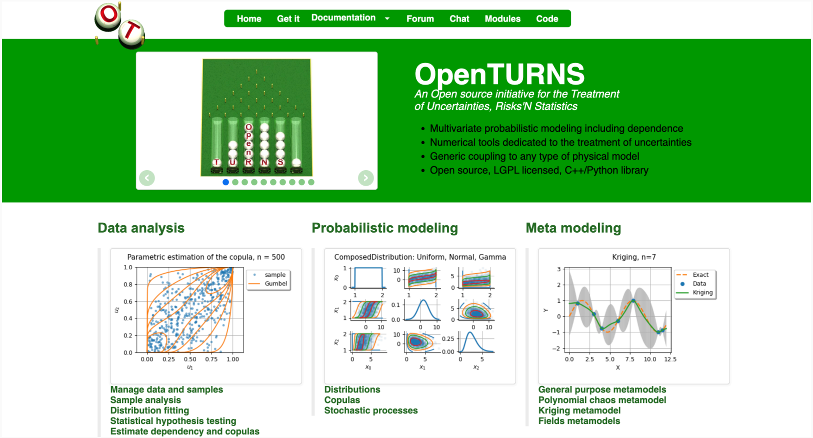


Figure 20: OpenTURNS' webpage.

OpenTURNS: an open-source library for UQ

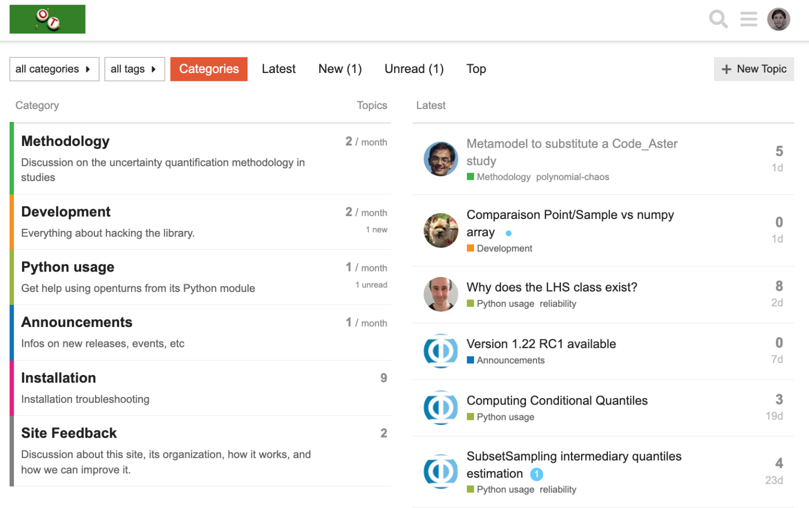


Figure 21: OpenTURNS' Discourse forum.

Persalys: an open-source GUI for UQ and data analysis

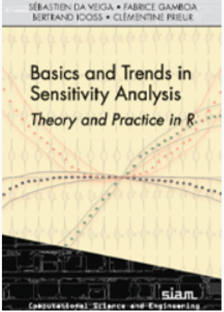
- **Persalys in a few words:**
  - GUI based on OpenTURNS
  - Interface available in French or in English
  - Open source software, developed by a partnership between **Phimeca & EDF** (and a collaboration with the OpenTURNS consortium)

Persalys

- **More information?**
  - Website: https://persalys.fr/index.php
    ☞ **Just fill in the form (Level 1) and download it for free!**
  - Github: https://github.com/persalys/persalys
  - Discourse: https://persalys.discourse.group/

‘sensitivity’: global sensitivity analysis and ML interpretability

- **‘sensitivity’ in a few words:**
  - R package for the **sensitivity analysis of model outputs**
  - Now contains a few methods for **ML interpretability** ☞ [ICT22]
  - Last version: 1.29.0 (Published: 2023-08-31)
  - Many contributors (academic / industrial / students)
  - Maintainer: Bertrand Iooss (EDF R&D)
  - Companion book ☞ [DGIP21]



- **More information?**
  - CRAN webpage: https://persalys.fr/index.php
  - Reference manual: https://cran.r-project.org/web/packages/sensitivity/sensitivity.pdf

Conclusion

Conclusion

- **A few (positive) take-home messages...**
  - ✔ UQ is now a mature field in several industrial fields (energy, aerospace, automotive, etc.)
  - ✔ UQ benefits from a (very) high-level of academic research (in probability, statistics, optimization, machine learning, signal processing, geometry, topology, ...)
  - ✔ Many open source tools and software are available!
    ⚠ Be careful about "blind/naive use" of these methods and tools!
  - ✔ Safety authorities and regulators recognize this field as being of major interest
- **... and a few (personal) disappointments**
  - ✘ UQ is still underrepresented in some fields
  - ✘ UQ suffers (sometimes) from a lack of attractiveness compared to ML

Conclusion

- **A few open questions and/or perspectives**
  - Going deeper into the links between UQ and ML:
    - Several connections about the way uncertainties are taken into account
    - On-going works about **kernel methods**
    - The use of **conformal prediction** for doing UQ in ML models
    - Strong links between **eXplainable AI** and **global sensitivity analysis**
    - Anomaly detection vs. rare event estimation, any links?
  - Hybridation between UQ and ML
    - Robustess of “Physics-informed” strategies (complex simulation models)
    - Hybridation using other methods than neural networks
  - Challenges for industrial UQ:
    - UQ for input/output fields
    - UQ and the “transposition” problem ($\approx$ transfer learning)
    - UQ based on images/videos
    - UQ for complex models (environmental, biological, etc.)

Scientific dissemination & the French UQ community?

◆ **Main organizations and networks**

- ❑ **GdR MASCOT-NUM** ➪ a French Research Group dealing with stochastic methods for the analysis of numerical codes
- ❑ **GIS LARTISSTE** ➪ a French Scientific Consortium about UQ @ Paris-Saclay
- ❑ **SINCLAIR AI Lab.** ➪ the Saclay INdustrial Collaborative Laboratory for Artificial Intelligence Research (SINCLAIR), gathering researchers from EDF, Thales and TotalEnergies
- ❑ **frENBIS** ➪ the French local network of the European Network for Business and Industrial Statistics (ENBIS)

◆ **Main seminars and scientific events**

- ❑ **UQSay seminars** ➪ series of online seminars on the broad area of UQ, ML and related topics
- ❑ **ETICS Annual Research Schools** ➪ Thematic Research School on Uncertainty in Scientific Computing

Thank your for your attention!

Any question?

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