



HAL
open science

Kernel-based quadrature applied to offshore wind turbine damage estimation

Elias Fekhari, Bertrand Iooss, Vincent Chabridon, Joseph Muré

► **To cite this version:**

Elias Fekhari, Bertrand Iooss, Vincent Chabridon, Joseph Muré. Kernel-based quadrature applied to offshore wind turbine damage estimation. MASCOT-NUM 2022, 2022, Clermont-Ferrand, France. hal-03713013

HAL Id: hal-03713013

<https://hal.science/hal-03713013v1>

Submitted on 4 Jul 2022

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Kernel-based quadrature applied to offshore wind turbine damage estimation

Elias Fekhari^{1, 2}, Bertrand Iooss^{1, 2}, Vincent Chabridon¹, Joseph Muré¹

¹EDF R&D - 6 quai Watier, Chatou, France

²Université Nice Côte d'Azur - 28 Avenue de Valrose, Nice, France



Industrial context & Problem statement

- EDF Renewables operates ~10 000 MW of wind turbine (WT) worldwide
 - New technologies (e.g., offshore floating WT), wind farms reaching end-of-life
- ↪ *Need probabilistic tools to optimize safety margins and asset management*

Chained simulation model

Expensive-to-evaluate deterministic computer model [3] (distributed on a cluster):

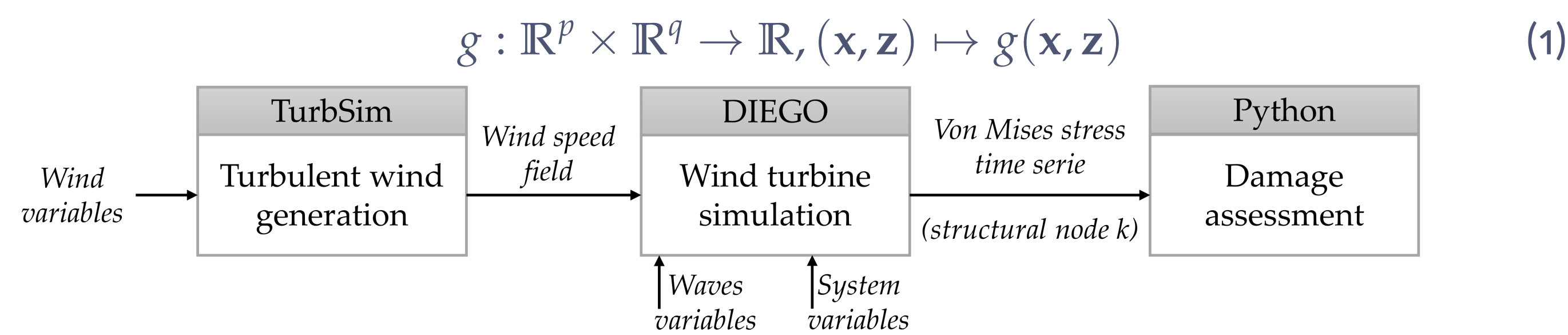


Fig. 1: Numerical simulation chain for WT damage assessment (simulates 10min)

Random inputs

- $\mathbf{X} \in \mathcal{D}_X \subset \mathbb{R}^p$: **environmental** random vector with its joint distribution $f_X(\cdot)$
- $\mathbf{Z} \in \mathcal{D}_Z \subset \mathbb{R}^q$: **system** random vector with its joint distribution $f_Z(\cdot)$
- The random vectors are considered **mutually independent**

Uncertainty propagation

Two **nested** quantities of interest to estimate (see [5])

Damage Equivalent Load (DEL): expected value of the damage over the environmental conditions (conditionally to a sample of system variables $\mathbf{Z} = \mathbf{z}$)

$$\mathbb{E}[Y|\mathbf{Z} = \mathbf{z}] = \mathbb{E}[g(\mathbf{X}, \mathbf{Z})|\mathbf{Z} = \mathbf{z}] = \int_{\mathcal{D}_X} g(\mathbf{x}, \mathbf{z}) f_X(\mathbf{x}) d\mathbf{x} = \phi(\mathbf{z}) \quad (2)$$

Probability of threshold exceedance: for a given threshold $y_{th} \in \mathbb{R}$

$$p_f = \mathbb{P}(\phi(\mathbf{Z}) > y_{th}) = \int_{\mathcal{D}_Z} \mathbb{1}_{\{\phi(\mathbf{z}) > y_{th}\}} f_Z(\mathbf{z}) d\mathbf{z} \quad (3)$$

↪ *How to efficiently estimate the DEL?*

Environmental measured data

SCADA data collected over a period of four years at the Teesside (UK) offshore wind farm

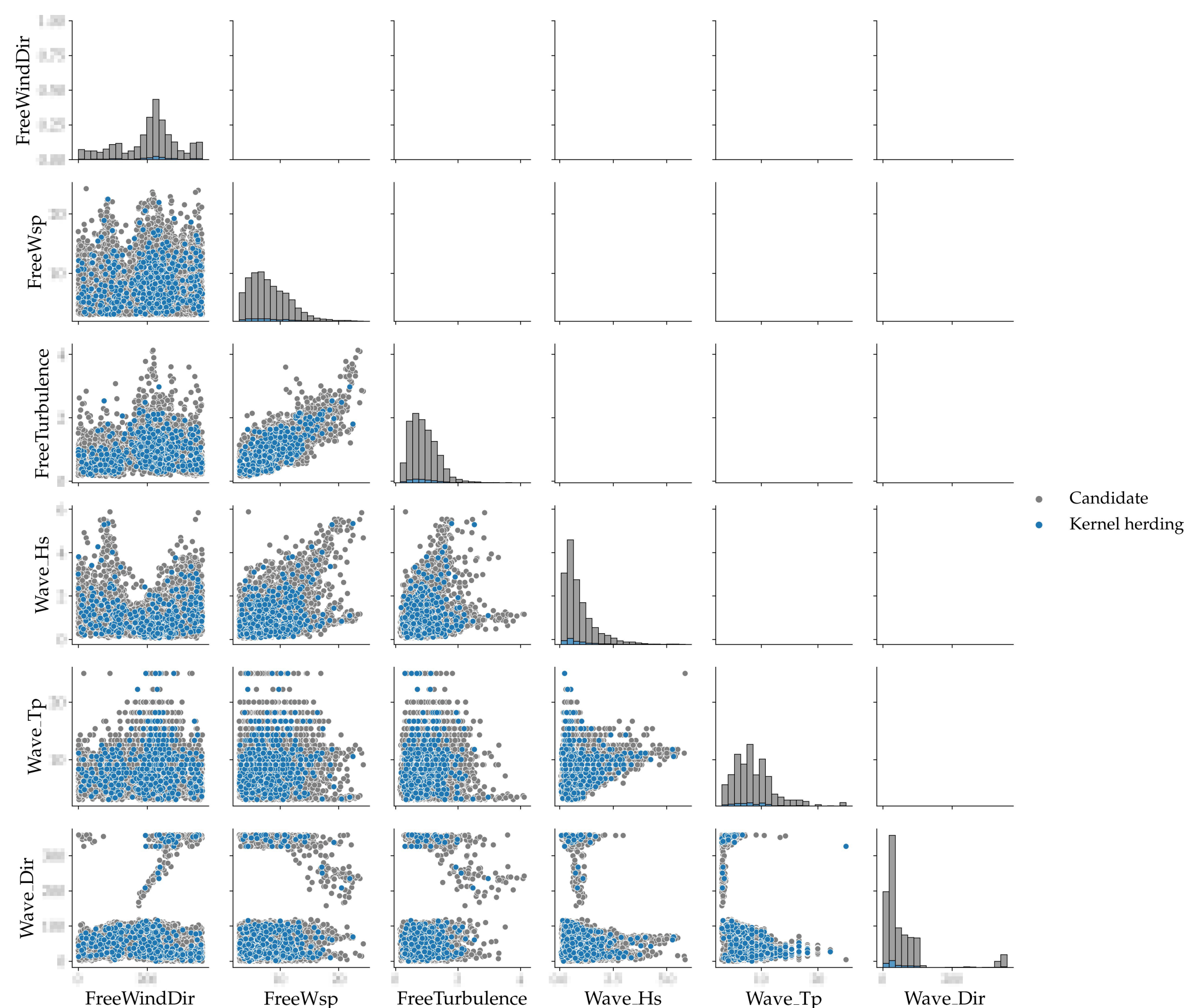


Fig. 2: Teesside wind farm environmental data (in grey, $N = 10^5$) and a kernel herding sample (in blue, $n = 520$)

Numerical results: DEL estimation by kernel herding

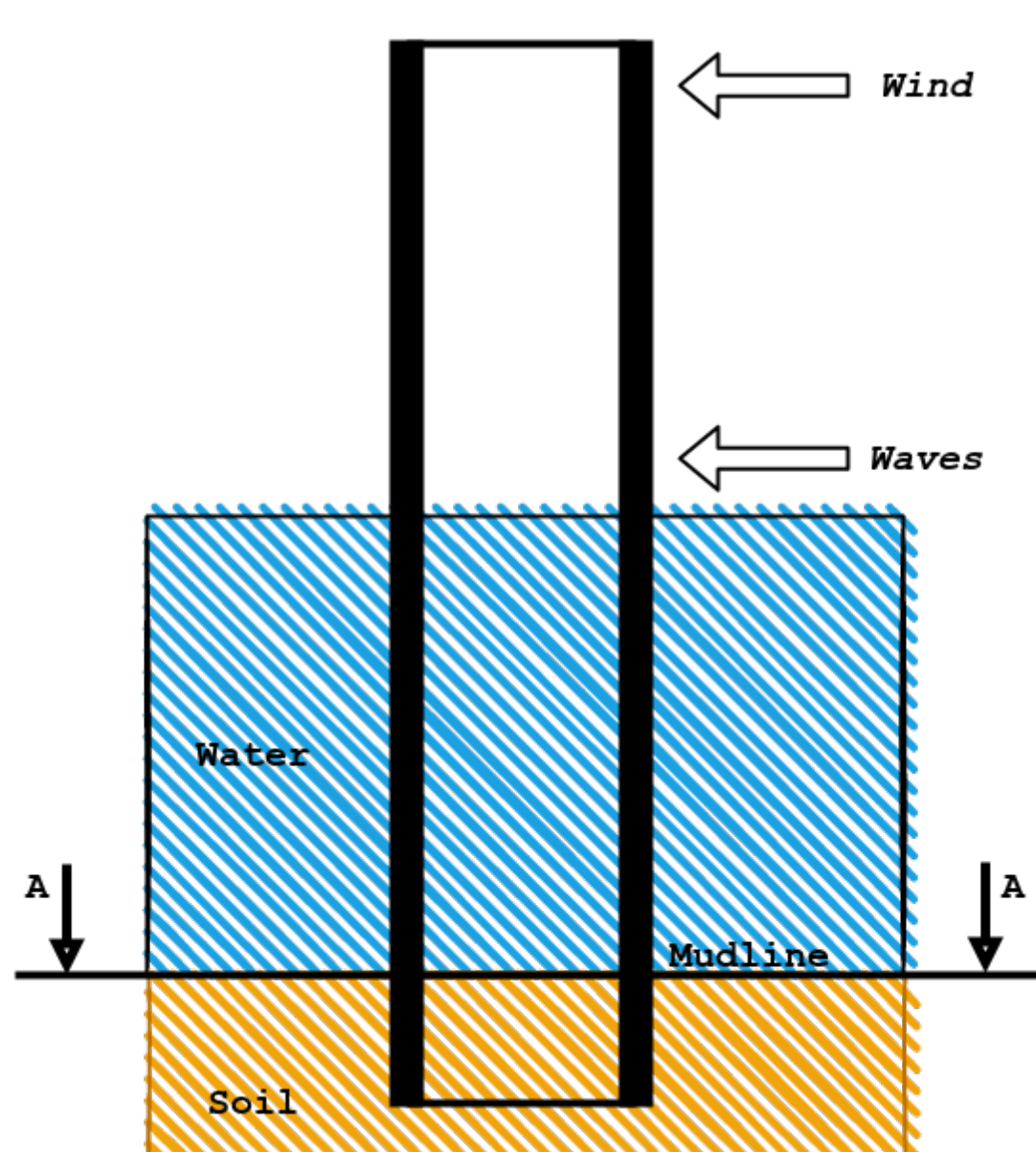


Fig. 4: Offshore wind turbine structure diagram

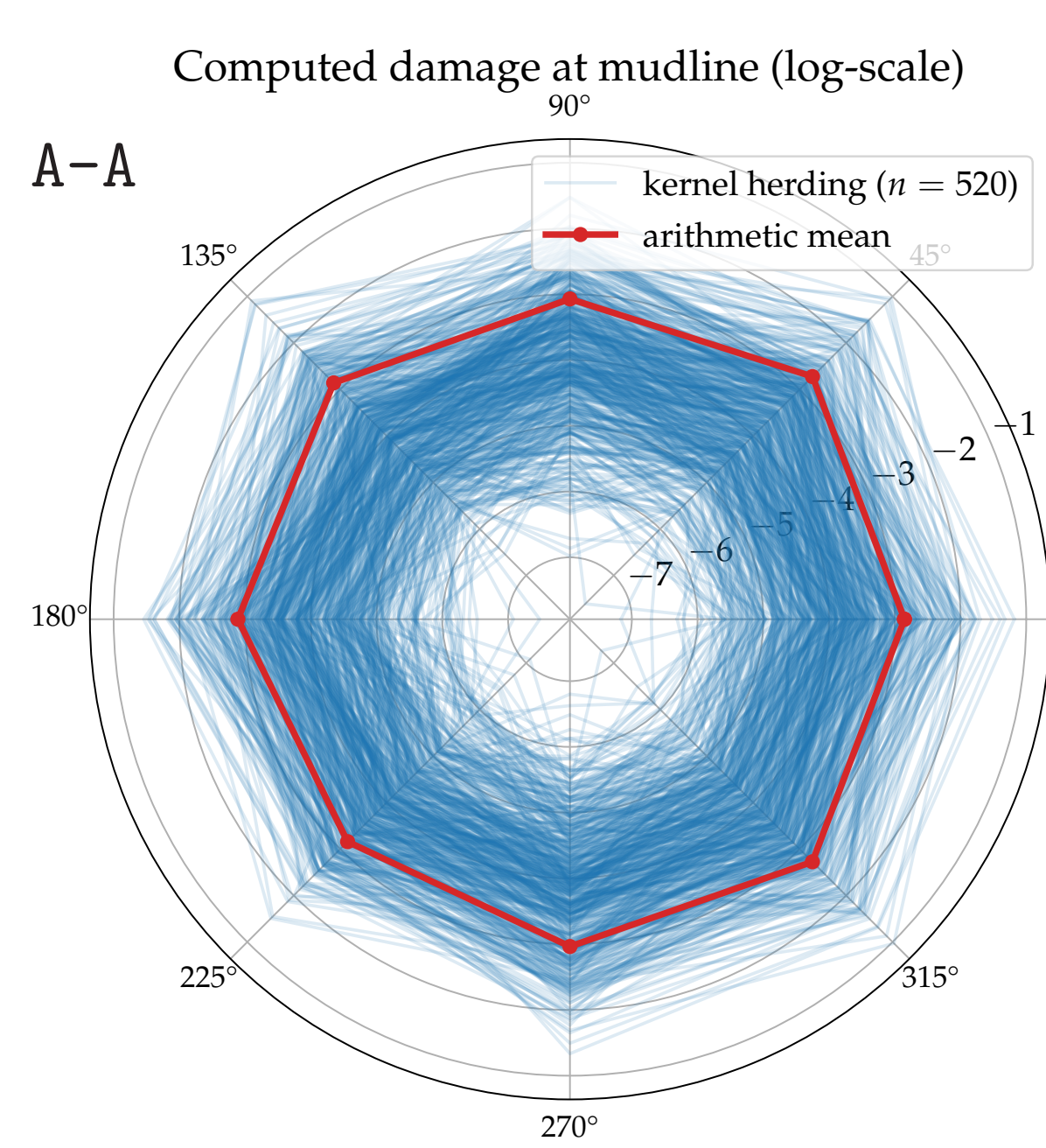


Fig. 5: Damage radar plot at the mudline

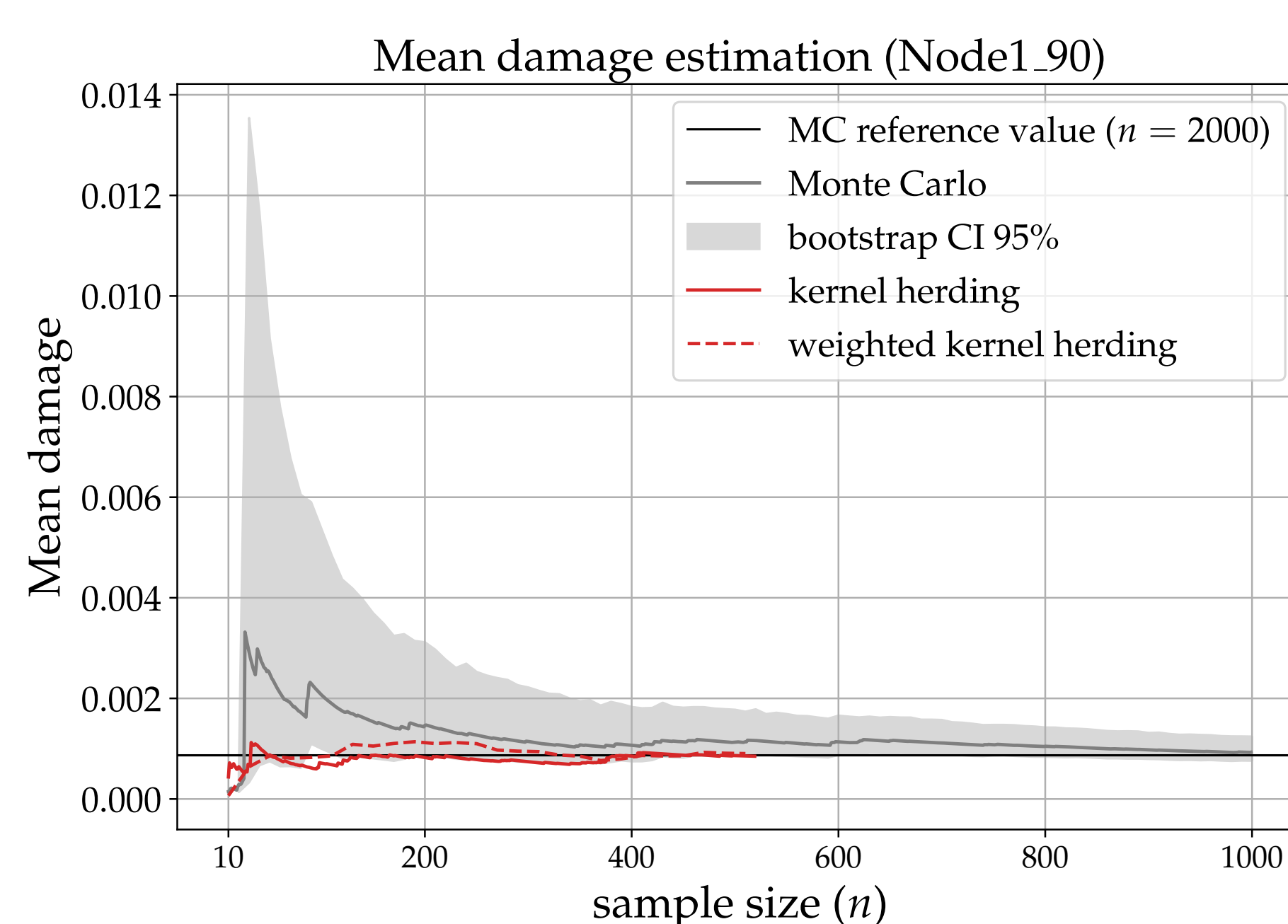


Fig. 6: Damage equivalent load estimation

Kernel-based probabilistic integration

$$1. \text{ Select integration nodes } \Rightarrow \mathbb{E}[g(\mathbf{X})] \approx \frac{1}{n} \sum_{i=1}^n g(\mathbf{x}^{(i)})$$

Candidate set: \mathcal{S} is a fairly dense finite subset of \mathbb{R}^d with size $N \gg n$ that emulates the target distribution (e.g., a large Sobol' sequence, available data as in Fig.2)

Kernel herding criterion [4, 6]: at iteration $n + 1$, for a given design of experiments (DoE) $\mathbf{X}_n = \{\mathbf{x}^{(1)}, \dots, \mathbf{x}^{(n)}\}$, and a given kernel k

$$\mathbf{x}^{(n+1)} \in \arg \min_{\mathbf{x} \in \mathcal{S}} \left(\frac{1}{n} \sum_{i=1}^n k(\mathbf{x}, \mathbf{x}^{(i)}) - \frac{1}{N} \sum_{j=1}^N k(\mathbf{x}, \mathbf{x}^{(j)}) \right) \quad (4)$$

$$2. \text{ Compute optimal weights for integration } \Rightarrow \mathbb{E}[g(\mathbf{X})] \approx \sum_{i=1}^n \mathbf{w}_i^* g(\mathbf{x}^{(i)})$$

Optimal weights for quadrature [2]: for a given DoE \mathbf{X}_n and a given kernel k

$$\mathbf{w}^* = P(\mathbf{X}_n) \mathbf{K}_n^{-1} \quad (5)$$

with potentials $P(\mathbf{X}_n) = [\int k(\mathbf{x}, \mathbf{x}^{(1)}) f_X(\mathbf{x}) d\mathbf{x}, \dots, \int k(\mathbf{x}, \mathbf{x}^{(n)}) f_X(\mathbf{x}) d\mathbf{x}]$ and variance-covariance matrix $\{\mathbf{K}_n\}_{i,j} = k(\mathbf{x}^{(i)}, \mathbf{x}^{(j)})$

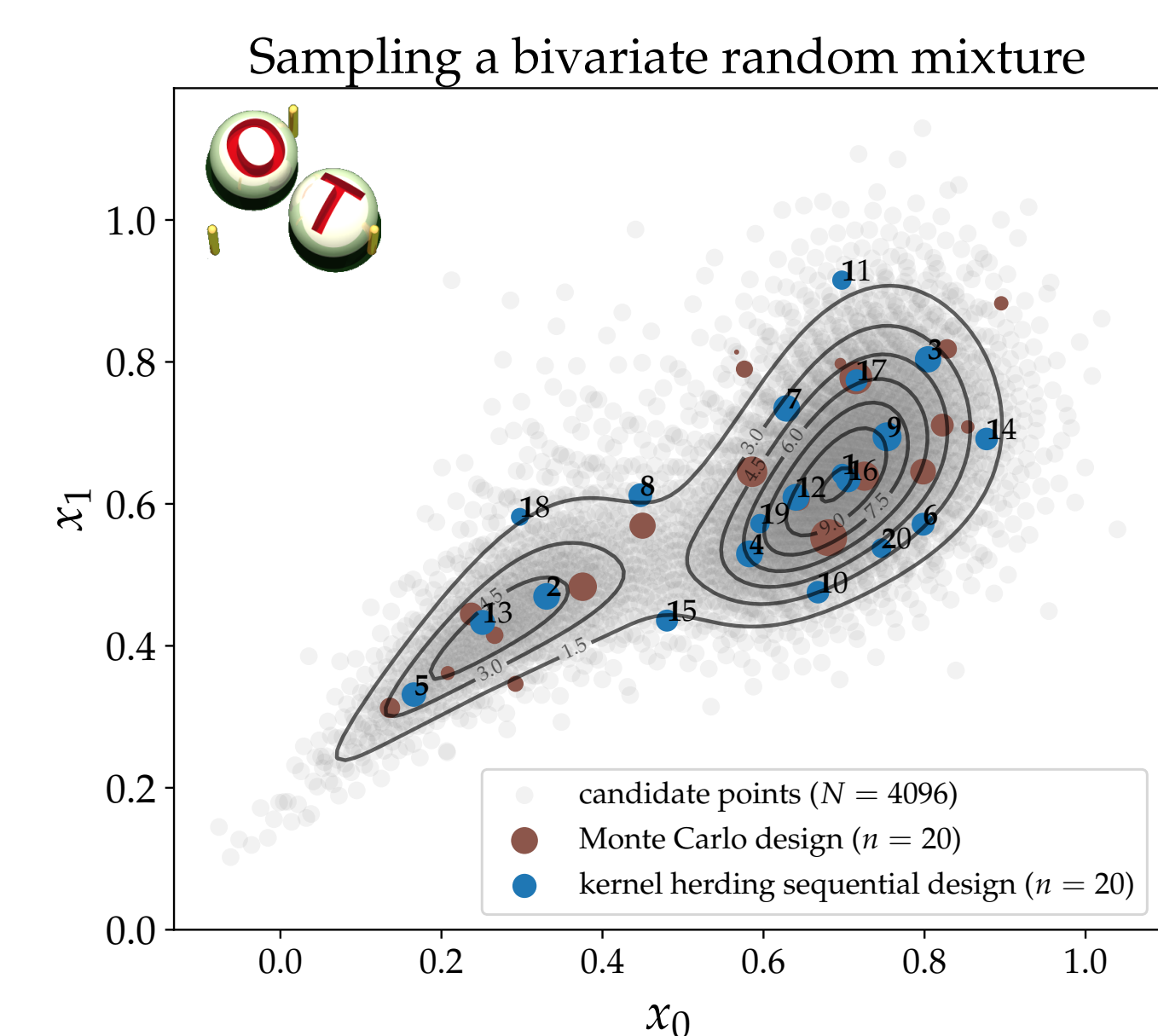


Fig. 3: Kernel-based sampling on a bivariate random mixture (markers' sizes indexed to the optimal weights)

↪ E. Fekhari et al. "Model predictivity assessment: incremental test-set selection and accuracy evaluation". In: *Preprint* (2021).

↪ New Python package on pypi: `otkerneldesign` (using OpenTURNS[1])

Conclusions & Perspectives

- Combining kernel herding with optimal weights is an efficient integration method
 - This method is sensitive to the chosen kernel and its hyper-parameters
 - This method allows direct sampling from available empirical distribution
 - Active learning methods might be more efficient but are harder to distribute (HPC)
- ↪ Determine influential system variables using advanced sensitivity analysis methods
- ↪ Adapt kernel-based sampling methods to reliability analysis problems

References

- [1] Michaël Baudin et al. "Title: Open TURNS: An industrial software for uncertainty quantification in simulation". In: *Handbook of uncertainty quantification*. 2017, pp. 1–38.
- [2] F.X. Briol et al. "Probabilistic Integration: A Role in Statistical Computation?" In: *Statistical Science* 34.1 (2019), pp. 1–22.
- [3] M. Capaldo et al. *Design brief of HIPERWIND offshore wind turbine cases: bottom fixed 10MW and floating 15MW*. Tech. rep. H2020 European project HIPERWIND, 2021.
- [4] Y. Chen, M. Welling, and A. Smola. "Super-samples from kernel herding". In: *Proceedings of the Twenty-Sixth Conference on Uncertainty in Artificial Intelligence*. AUAI Press, 2010, pp. 109–116.
- [5] K. Müller and P. Cheng. "Application of a Monte Carlo procedure for probabilistic fatigue design of floating offshore wind turbines". In: *Wind Energy Science* 3 (2018), pp. 149–162.
- [6] L. Pronzato and A.A. Zhigljavsky. "Bayesian quadrature and energy minimization for space-filling design". In: *SIAM/ASA Journal on Uncertainty Quantification* 8 (2020), pp. 959–1011.