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Kernel-based quadrature applied to offshore wind turbine damage estimation

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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):

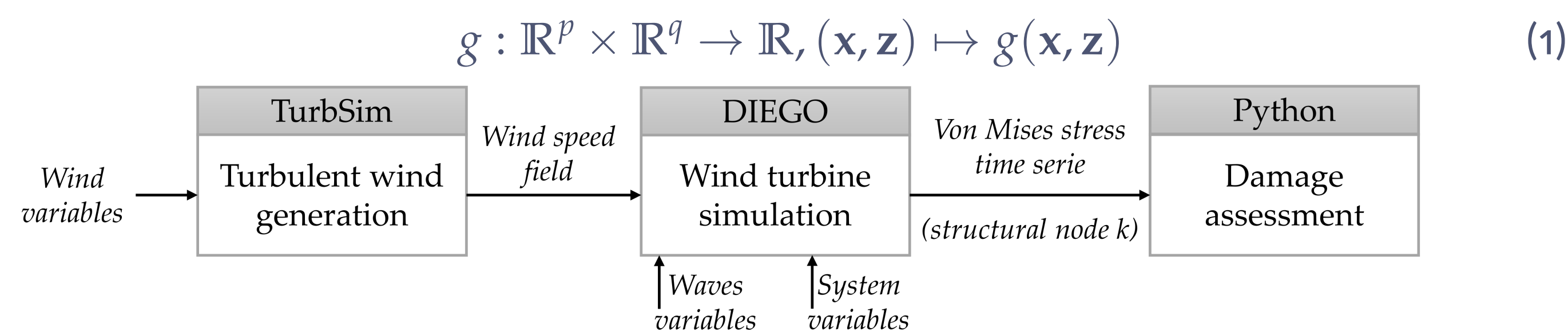


Fig. 1: Numerical simulation chain for WT damage assessment (simulates 10min)

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

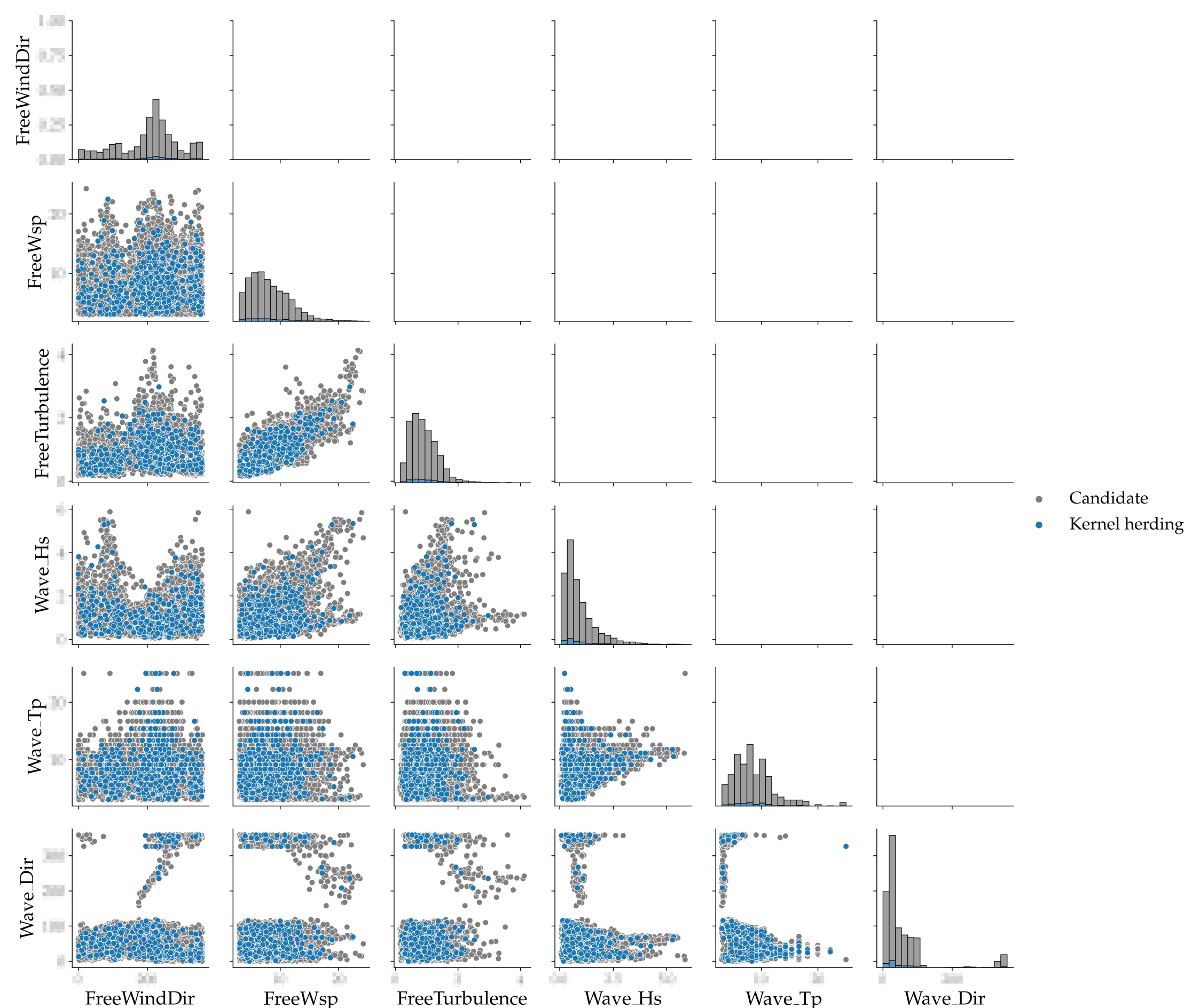


Fig. 2: Teesside wind farm environmental data (in grey, $N = 10^5$) and a kernel herding sample (in blue, $n = 520$)

Numerical results: DEL estimation by kernel herding

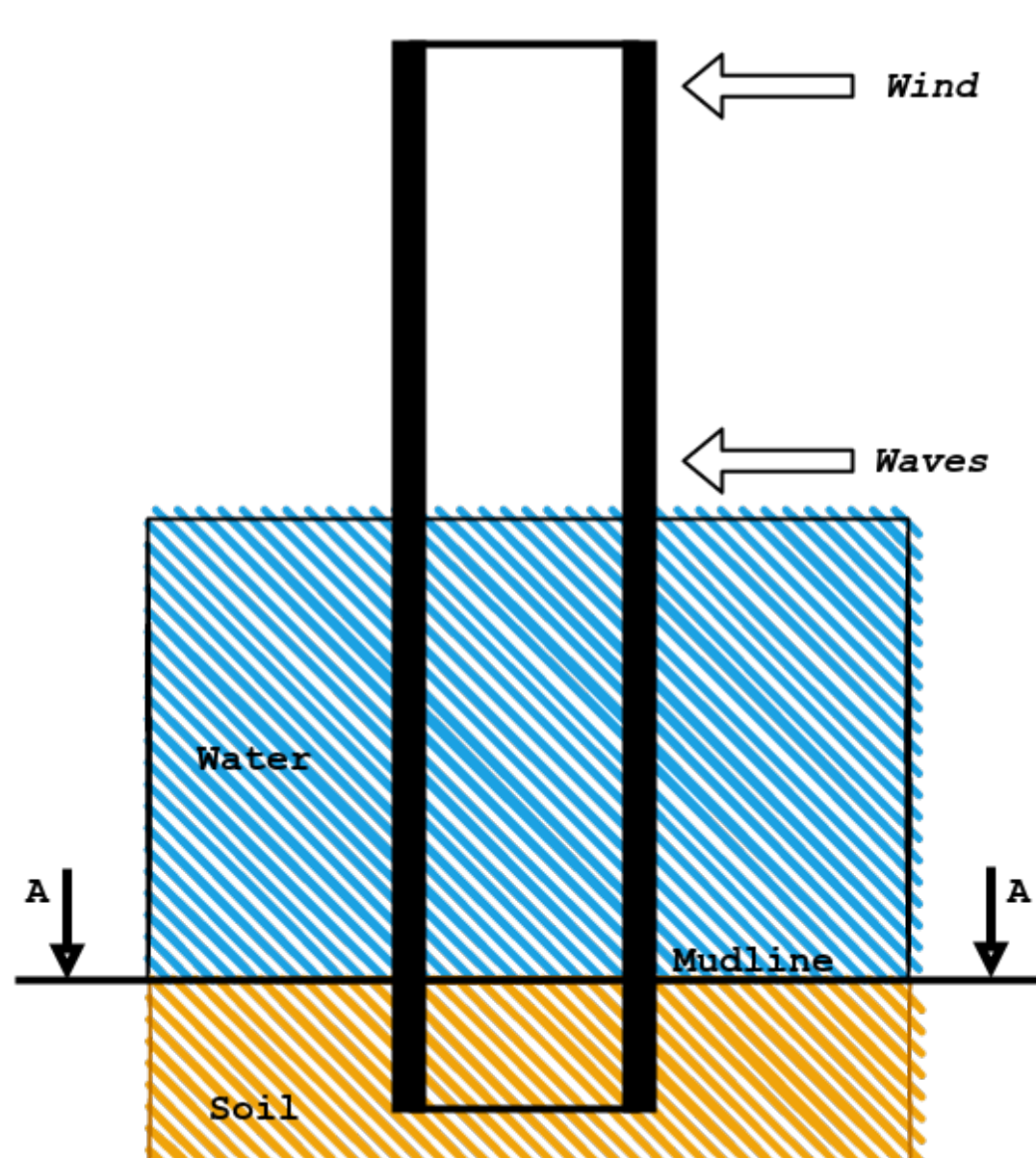


Fig. 4: Offshore wind turbine structure diagram

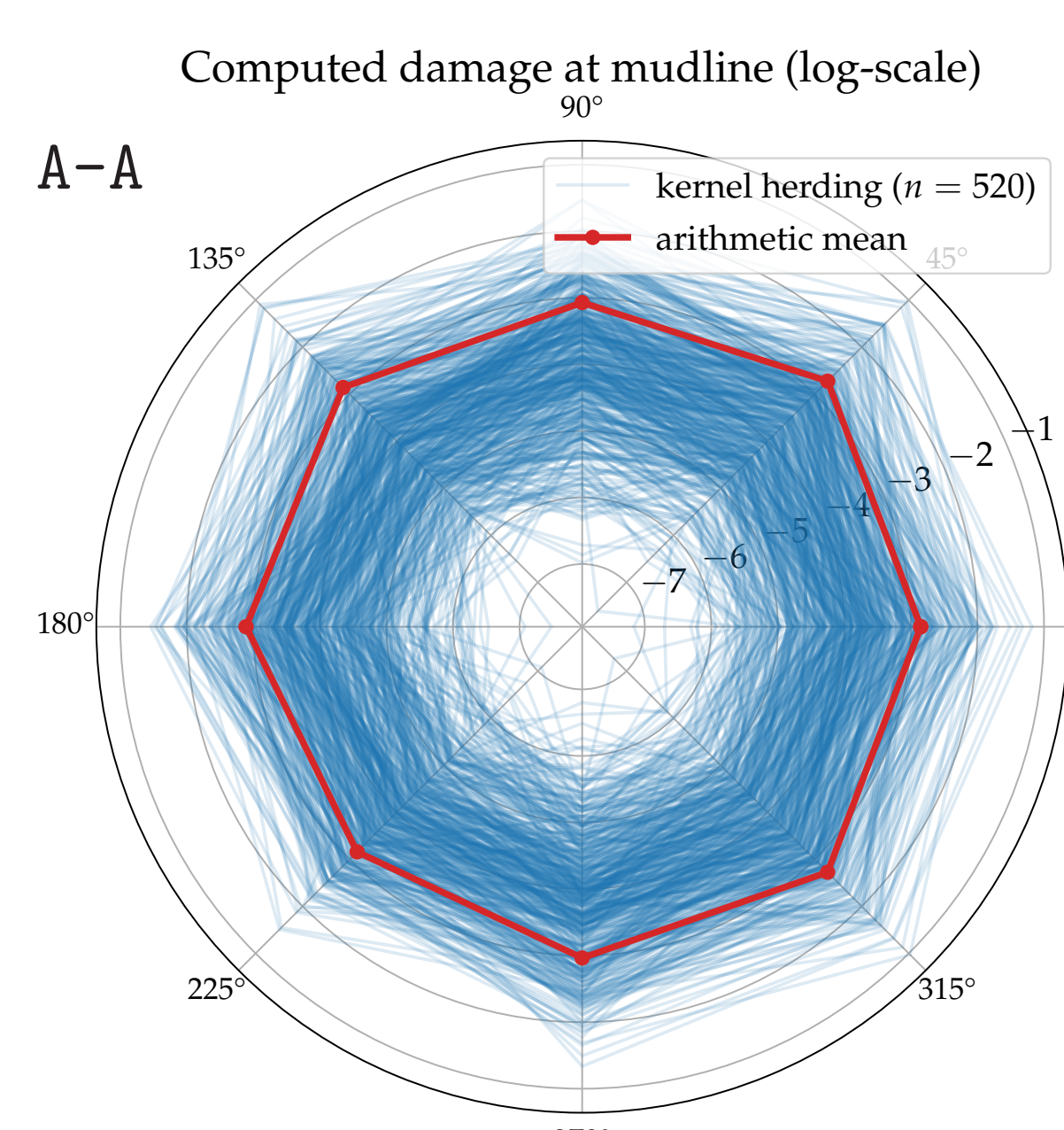


Fig. 5: Damage radar plot at the mudline

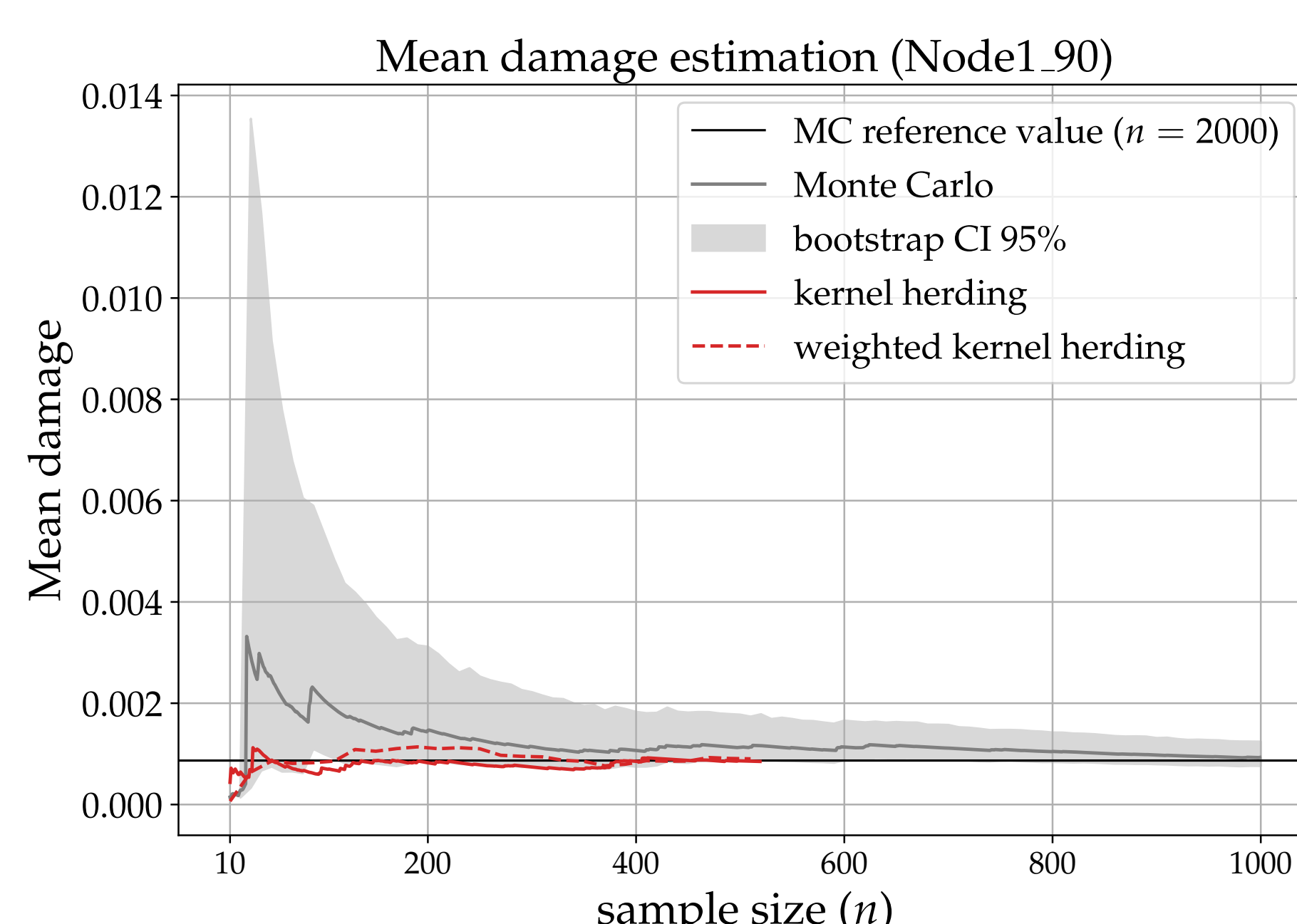


Fig. 6: Damage equivalent load estimation

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 $\{\mathbf{K}_n\}_{i,j} = k(\mathbf{x}^{(i)}, \mathbf{x}^{(j)})$

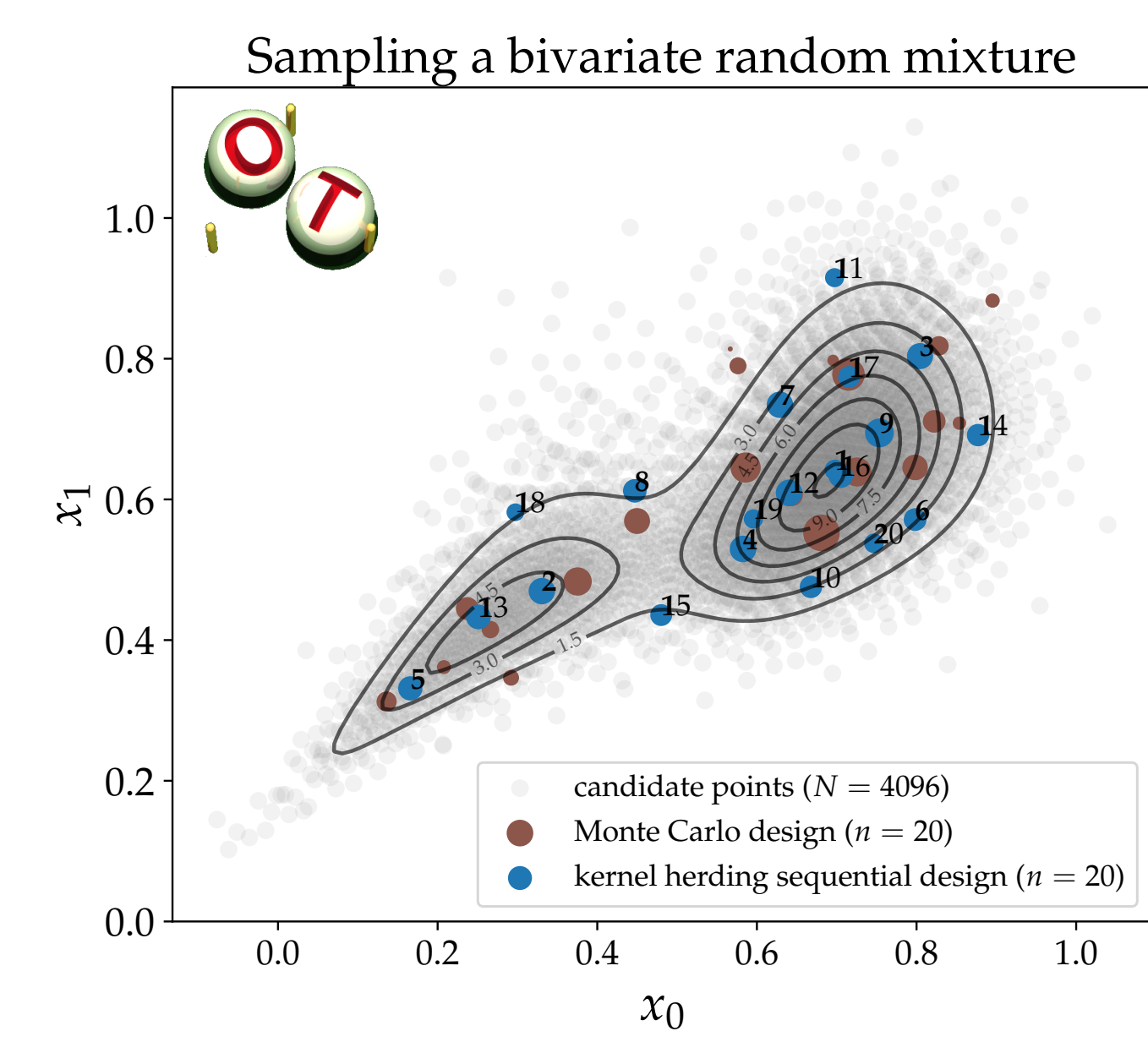


Fig. 3: Kernel-based sampling on a bivariate random mixture (markers' sizes indexed to the optimal weights)

↪ 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

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