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):

$$g : \mathbb{R}^p \times \mathbb{R}^q \to \mathbb{R}, (\mathbf{x}, \mathbf{z}) \mapsto g(\mathbf{x}, \mathbf{z}) \quad (1)$$

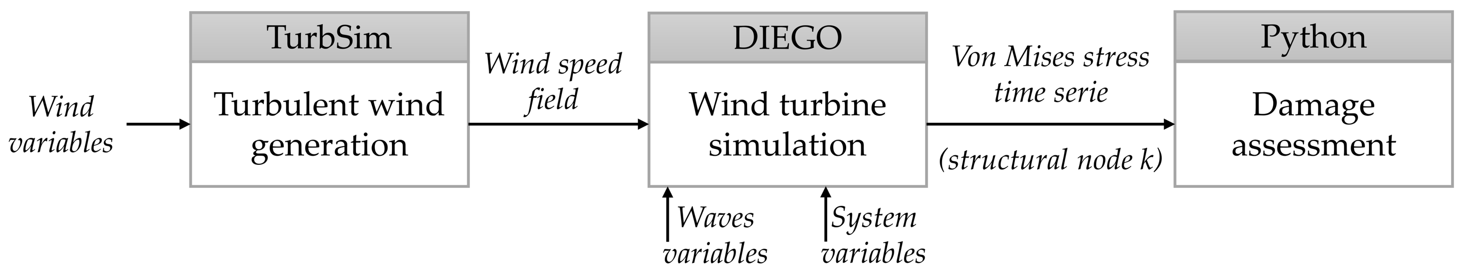

Fig. 1: Numerical simulation chain for WT damage assessment (simulates 10min)

Random inputs

- $\mathbf{X} \in \mathcal{D}_{\mathbf{X}} \subset \mathbb{R}^p$: environmental random vector with its joint distribution $f_{\mathbf{X}}(\cdot)$
- $\mathbf{Z} \in \mathcal{D}_{\mathbf{Z}} \subset \mathbb{R}^q$: system random vector with its joint distribution $f_{\mathbf{Z}}(\cdot)$
- 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 $\mathbf{Z} = \mathbf{z}$)

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

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

$$p_{\text{f}} = \mathbb{P}\left(\phi(\mathbf{Z}) > y_{\text{th}}\right) = \int_{\mathcal{D}_{\mathbf{Z}}} \mathbb{1}_{\{\phi(\mathbf{z}) > y_{\text{th}}\}} f_{\mathbf{Z}}(\mathbf{z})\, \mathrm{d}\mathbf{z} \quad (3)$$

↪ *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

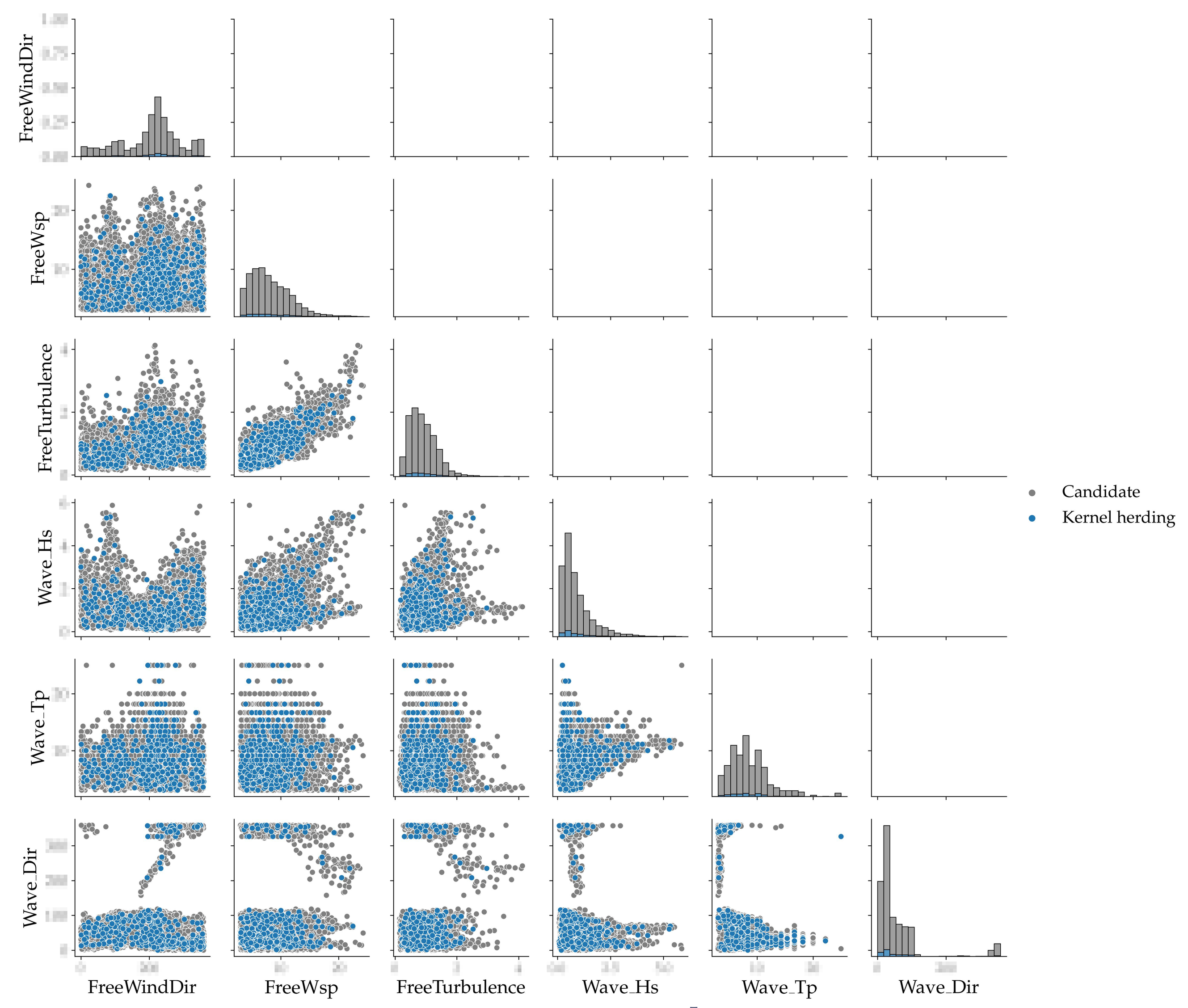

Fig. 2: Teesside wind farm environmental data (in grey, $N = 10^5$) and a kernel herding sample (in blue, $n = 520$)

Kernel-based probabilistic integration

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

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

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

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

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

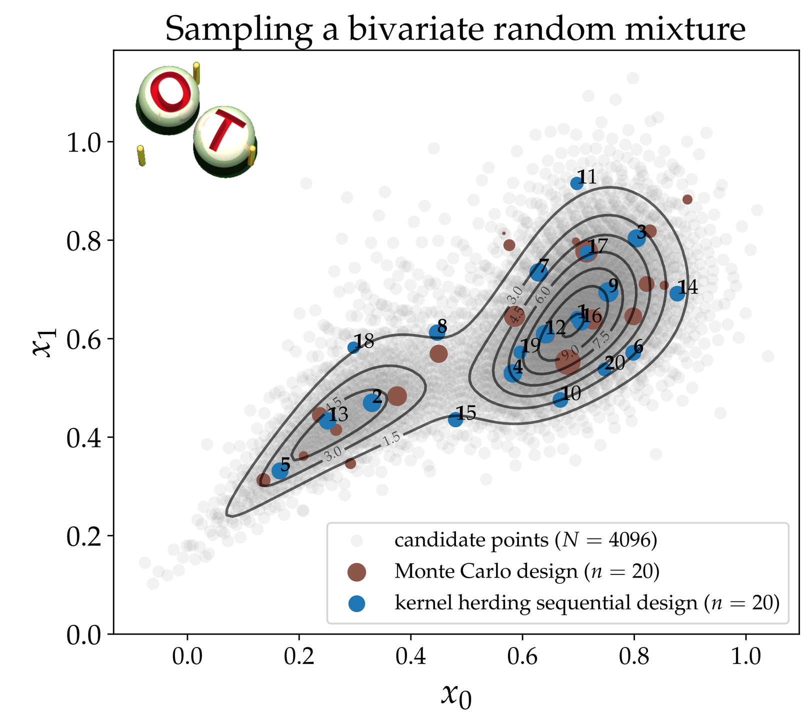

Fig. 3: Kernel-based sampling on a bivariate random mixture (markers' sizes indexed to the optimal weights)

↪ 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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[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.
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Numerical results: DEL estimation by kernel herding

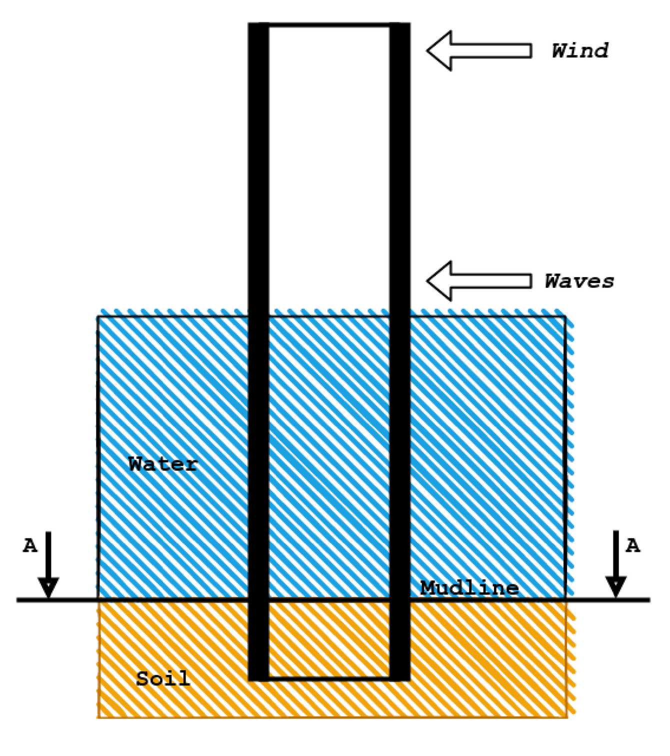

Fig. 4: Offshore wind turbine structure diagram

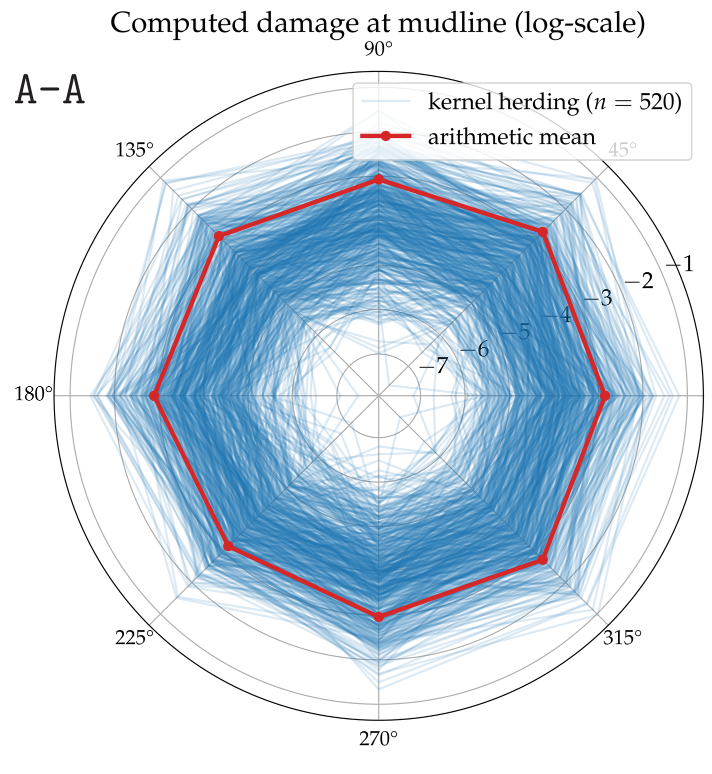

Fig. 5: Damage radar plot at the mudline

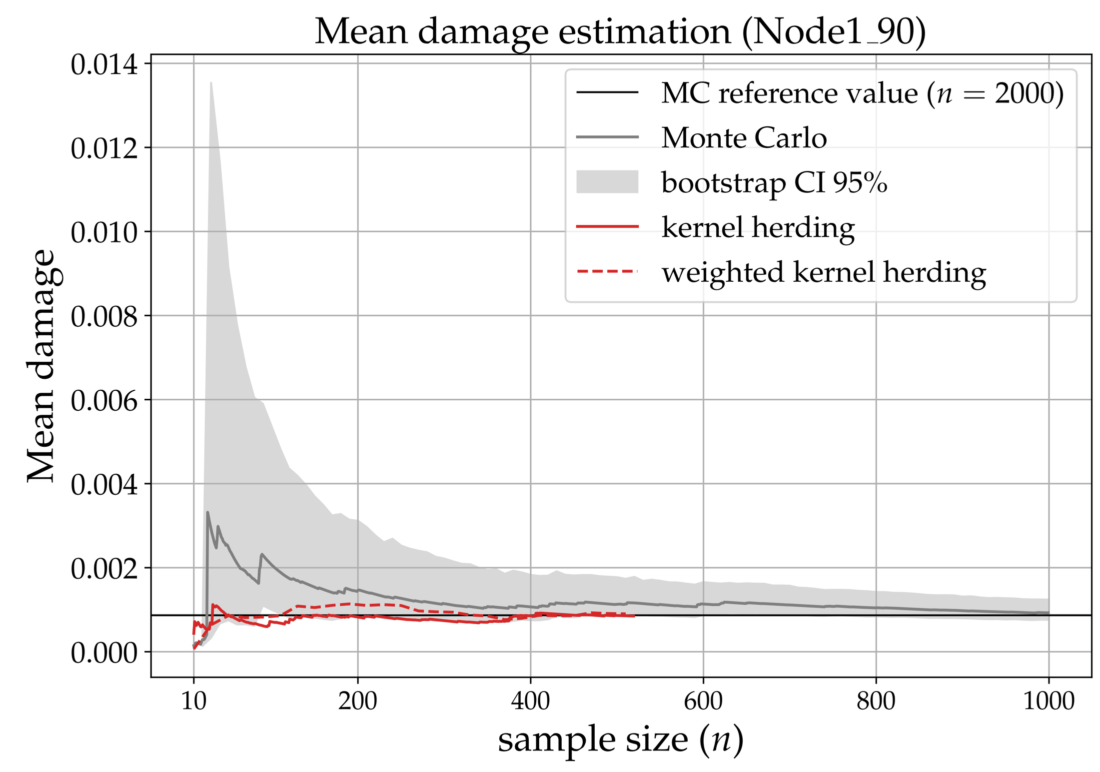

Fig. 6: Damage equivalent load estimation