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Kernel-based sequential quadrature methods applied to offshore wind turbine damage estimation

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Abstract:

Offshore wind turbine (OWT) new technologies tend to reach for more difficult and uncertain environmental conditions. This industry needs probabilistic tools to manage risks associated with OWT operation and maintenance. In this thesis, the OWT behavior is computed by a transient costly multi-physics numerical simulation code deployed on a high-performance computer facility. In fact, EDF R&D has implemented a computer simulation chain composed of two simulation tools: the first one called TurbSim, developed by NREL, is a stochastic wind generator; the second one, called DIEGO (for "Dynamique Intégrée des Éoliennes et Génératrices Offshore") and developed by EDF R&D, is a multi-physics code describing the hydro-aero-servo-elastic behavior of a OWT.

To propagate the various sources of uncertainties through such numerical models, identifying the best sample to estimate a specific quantity of interest is of prime importance. Historically, sampling methods such as low-discrepancy sequences (e.g., Sobol' sequences) were proven to improve the Monte Carlo reference convergence rate. An alternative strategy is to emulate the costly function by a surrogate regression model. For instance, using a Gaussian process regression model provides an estimation of the regression error represented by the variance of the Gaussian process conditioned to the learning sample. This property is extensively exploited by adaptive methods for optimization, rare event, and quadrature estimation to iteratively choose input samples with respect to a specific goal.

Uncertainty propagation has been widely applied to similar WT models to study the mechanical fatigue damage of the structure in a central tendency study [4, 2], a sensitivity analysis or a reliability analysis [5]. In this case, the uncertainty propagation is at least composed of two steps: first, to estimate the expected value with respect to random environmental variables for any given set of design variables. Second, to perform a reliability analysis by considering these design variables as random. Each step has a wide literature to deal with costly numerical models. Regarding the first step, the standards recommend computing realizations of the damage for a set of inputs discretized over a regular grid [2]. However, regular grids are known to provide poor probabilistic design of experiments for any input dimension higher than one.

During the beginning of this thesis, our aim was to perform a numerical comparison between various quadrature methods to estimate the expected value of the fatigue damage of an OWT over environmental random variables. Additionally, theoretical equivalences between Bayesian quadrature and Maximum Mean Discrepancy-based sampling methods (such as Kernel Herding, and Support Points see [1]) were studied. Whether they progressively require output observations (supervised) or not (unsupervised), the different adaptive methods for quadrature can be defined by their learning function. Assuming that $(\mathbf{X}_n, \mathbf{y}_n)$ is an initial design of experiments of size $n \in \mathbb{N}$ and its respective realizations of a simulation model, the learning function $\mathcal{A}$ is the criteria driving the next point selection. At each step, this selection can be done by a greedy optimization on a fairly dense finite sample $\mathcal{S} \subset \mathbb{R}^d$ with size $N \gg n$ that represents the distribution as follows:

$$\mathbf{x}_{n+1} \in \underset{\mathbf{x} \in \mathcal{S}}{\arg\max}\, \mathcal{A}\left(\mathbf{x} \mid (\mathbf{X}_n, \mathbf{y}_n)\right). \tag{1}$$

Interestingly, theoretical equivalences were already uncovered between a weighted version of the unsupervised Kernel Herding sampling and the Sequential Bayesian quadrature [3]. These results are illustrated in Figure 1 on a numerical toy example. In this Figure, one can see, on the left, the numerical integration of a two-dimensional function (colored contours) against a complex input distribution (black iso-probability contours). Moreover, still on the left, the black crosses illustrate a Kernel Herding sample of the distribution. Meanwhile, on the right, the convergence of various estimators of output expected values are represented: the reference Sobol' sequence (in green), the Kernel Herding (in black) and the same Kernel Herding but optimally-weighted (in dashed black). This example exposes the benefit of coupling kernel-based sampling methods with optimal weights to estimate an output expected value. Additionally, this technique presents the practical advantage of being unsupervised, allowing to run all the simulation apart from the design construction.

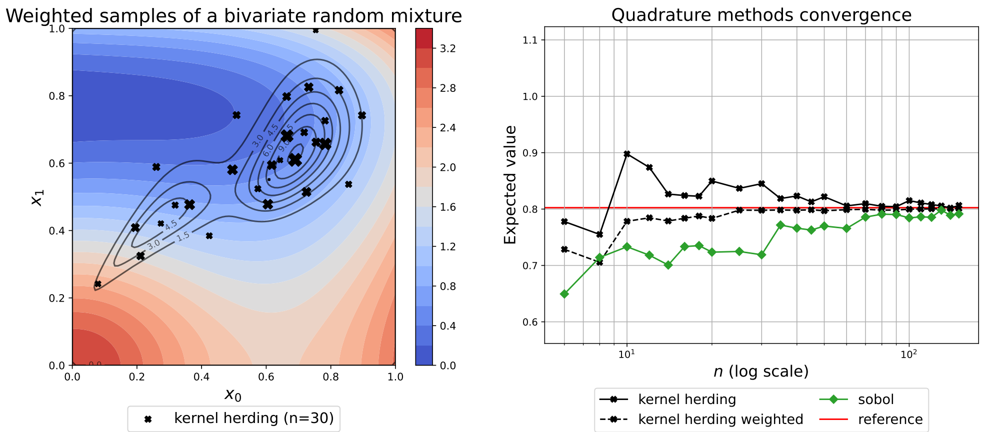

Figure 1: Optimally-weighted Kernel Herding sampling of a bivariate random mixture

If these recent algorithms have been widely used on toy cases, they remain underused in real industrial applications. The proposed work aims at presenting two contributions: the first one consists in investigating the performance of these algorithms on a challenging industrial OWT damage assessment use case, and the second one, more methodological, is to provide other learning criteria as in Eq.(1) to efficiently solve these problems by taking advantage of strong links with other adaptive strategies.

References

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Short biography – After graduating from the French Institute for Advanced Mechanics (now SIGMA Clermont) with an Engineer's degree, I joined the R&D lab of the French electric utility company EDF. I worked for three years as a research engineer in applied Mathematics for industrial risk management before starting a Ph.D. on the treatment of uncertainties in simulation models for wind turbine asset management.