Application 1: Design of floating wind farms

ANR GATSBII – GAme Theory and Statistical estimation Bring Importance measures and Interpretability

Elias FEKHARI[1]

[1]EDF R&D, EDF Lab Chatou
Département PRISME
(Performance, Risque Industriel et Surveillance pour la Maintenance et l'Exploitation)
Groupe P17 GAIA
(Gestion d'Actifs, Incertitudes et Apprentissage statistique)

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- **Offshore wind energy at EDF:**
  - ❑ EDF is a major actor of the offshore wind turbine development
  - ❑ Need to take strategic decisions in uncertain conditions
    - For asset management (e.g., to extend a wind farm operating time)
    - For probabilistic design (e.g., to optimize the geometry of floaters)
  - ❑ EDF R&D Participate to HIPERWIND[1] (EU research project)

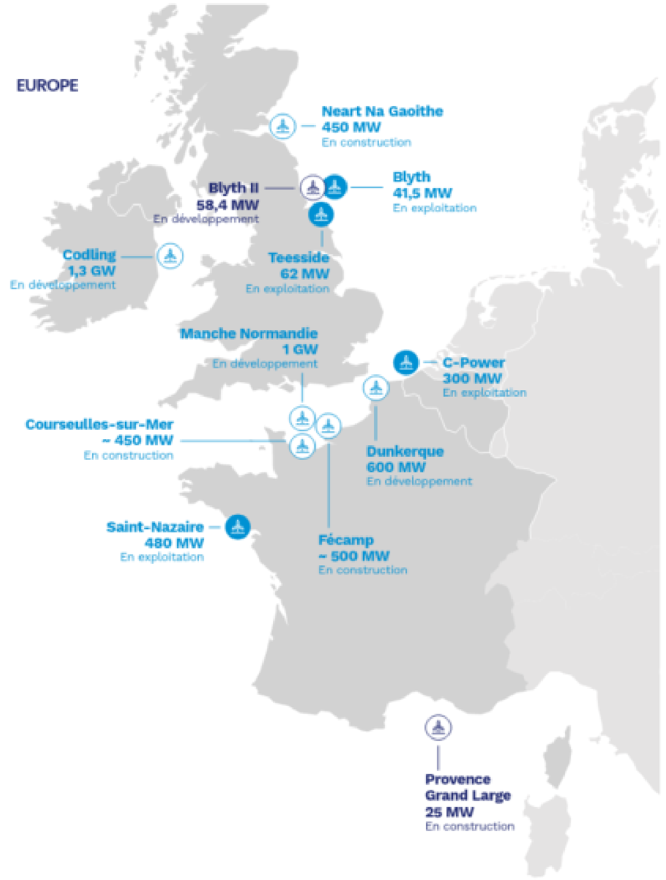

Figure 1: Map of offshore wind farms and projects operated by EDF in Europe (source: EDF Renewables).

[1] HIPERWIND project website: `hiperwind.eu`

Available resources

❑ In situ metocean data

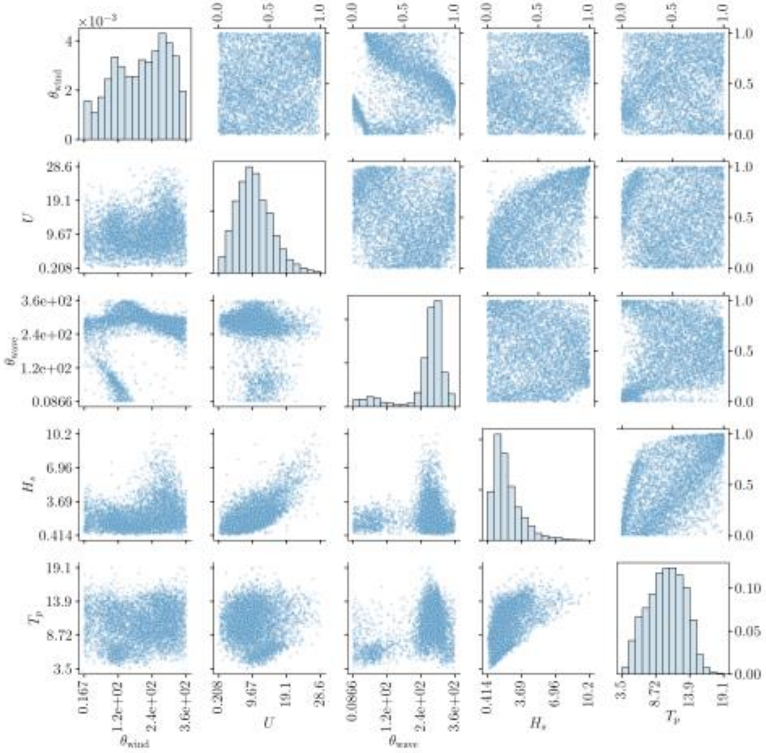

Figure 3: Copulogram of the South Brittany metocean data ($N = 10^4$).

❑ Numerical simulation models

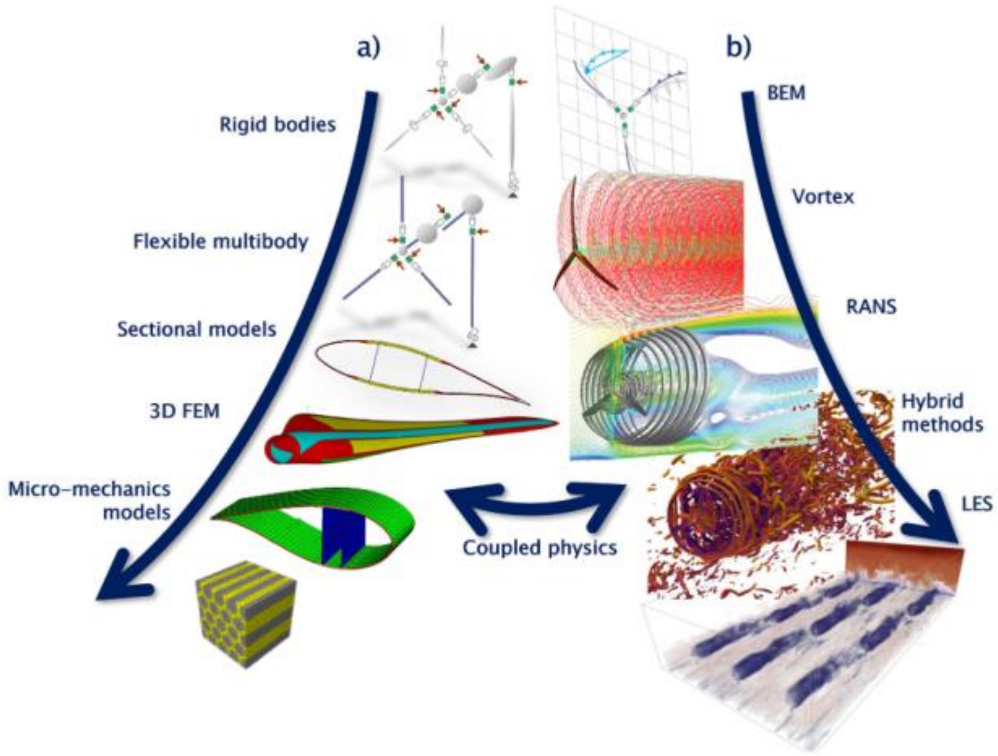

Figure 4: Hierarchy of structural (a) and aerodynamic (b) wind energy systems models (source: [Veers et al., 2019]).

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Focus on offshore wind turbine numerical simulator

- Wind turbine chained model studied:
  - **Uncertain inputs:** metocean vector $\mathbf{x}$ (i.e., wind and waves) and system vector $\mathbf{z}$ (e.g., nacelle misalignement)
  - **Output of interest:** cumulative damage over 10 minutes $d_{\mathrm{c}}^{10\mathrm{min}}$ at a critical node of the structure (mudline)

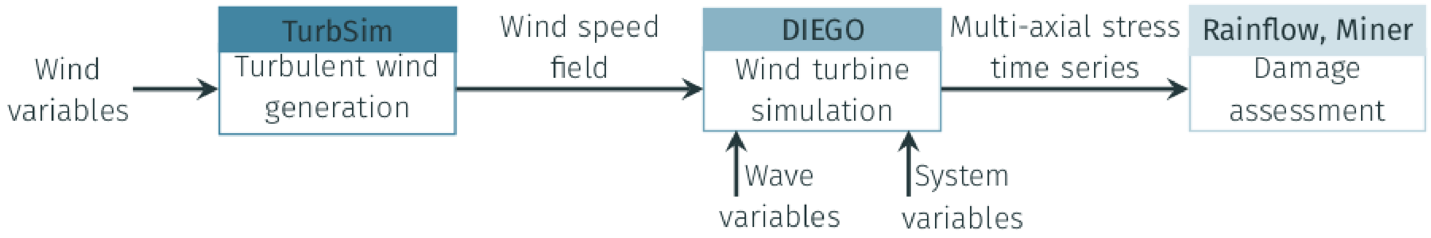

Figure 5: Diagram of the chained wind turbine simulation model.

$$d_{\mathrm{c}}^{10\mathrm{min}} : \left| \begin{array}{ccc} \mathbb{R}^p \times \mathbb{R}^q & \to & \mathbb{R} \\ (\mathbf{x}, \mathbf{z}) & \mapsto & d_{\mathrm{c}}^{10\mathrm{min}}(\mathbf{x}, \mathbf{z}) \end{array} \right.$$

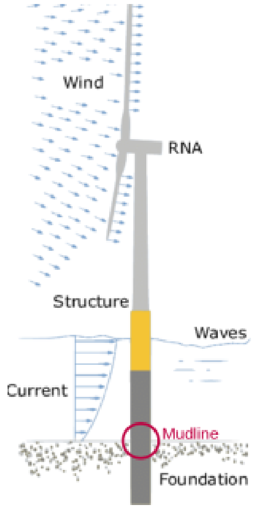

Figure 6: Monopile offshore wind turbine diagram (source: [Page et al., 2018]).

[2] "Dynamique Intégrée des Éoliennes et Génératrices Offshore"

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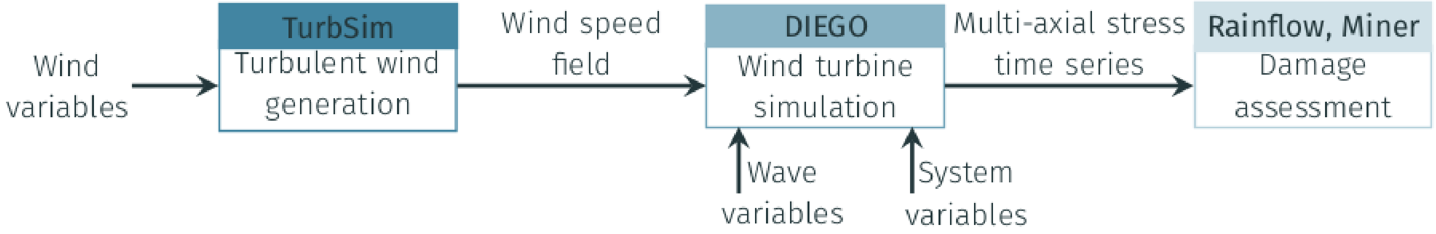

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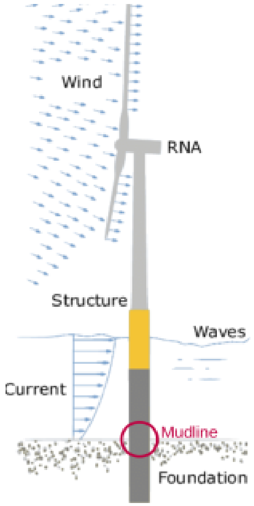

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  - **Multiphysics model:** DIEGO[2] performs time-dependent simulations of a bottom-fixed wind turbine
  - **Model validation:** benchmark with similar codes (OpenFAST, HAWC2, etc. [Kim et al., 2022])
  - **Stochasticity of the turbulent wind generation:** each evaluation is repeated $n_{\mathrm{reps}} = 11$ times

[2] "Dynamique Intégrée des Éoliennes et Génératrices Offshore"

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Metocean datasets used during my PhD

- Operating wind farm in Teesside (UK)
  - Measurements of metocean data (confidential data)
  - Old wind turbine model
- Wind farm tender in South Brittany (France)
  - Simulated metocean data (public data from *ANEMOC: Atlas des États de Mer Océaniques et Côtiers*)

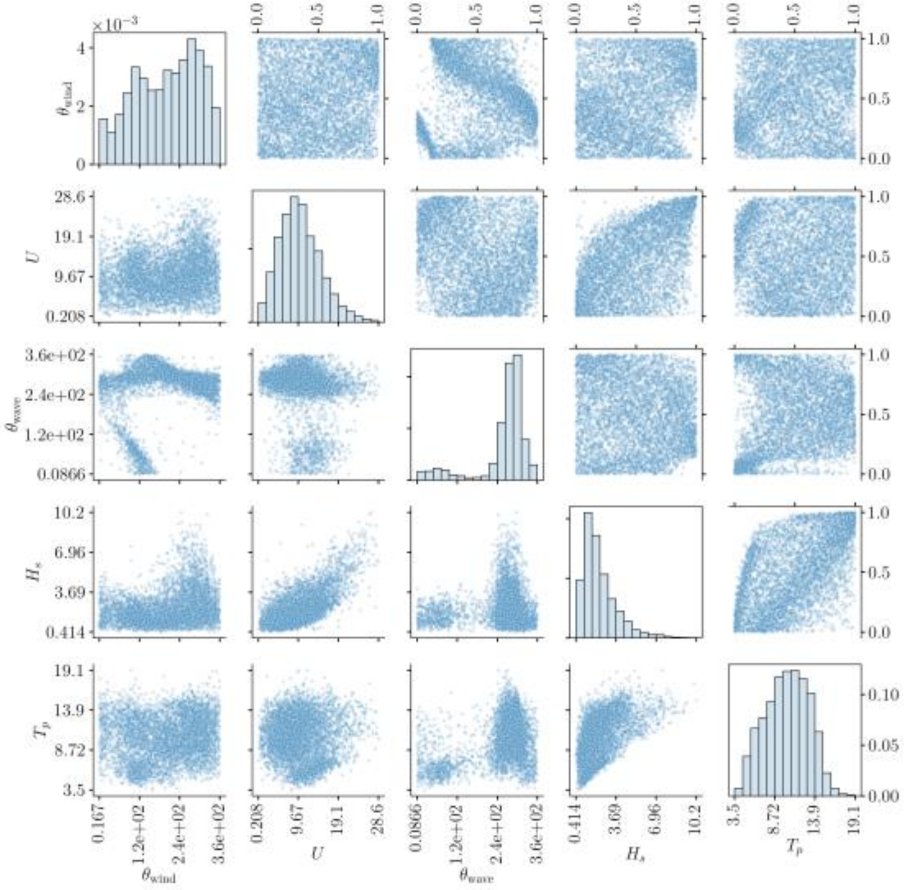
Example of multivariate inference on the South Brittany data

- Marginals by parametric or nonparametric methods
- Multivariate dependence structure by nonparametric empirical copula

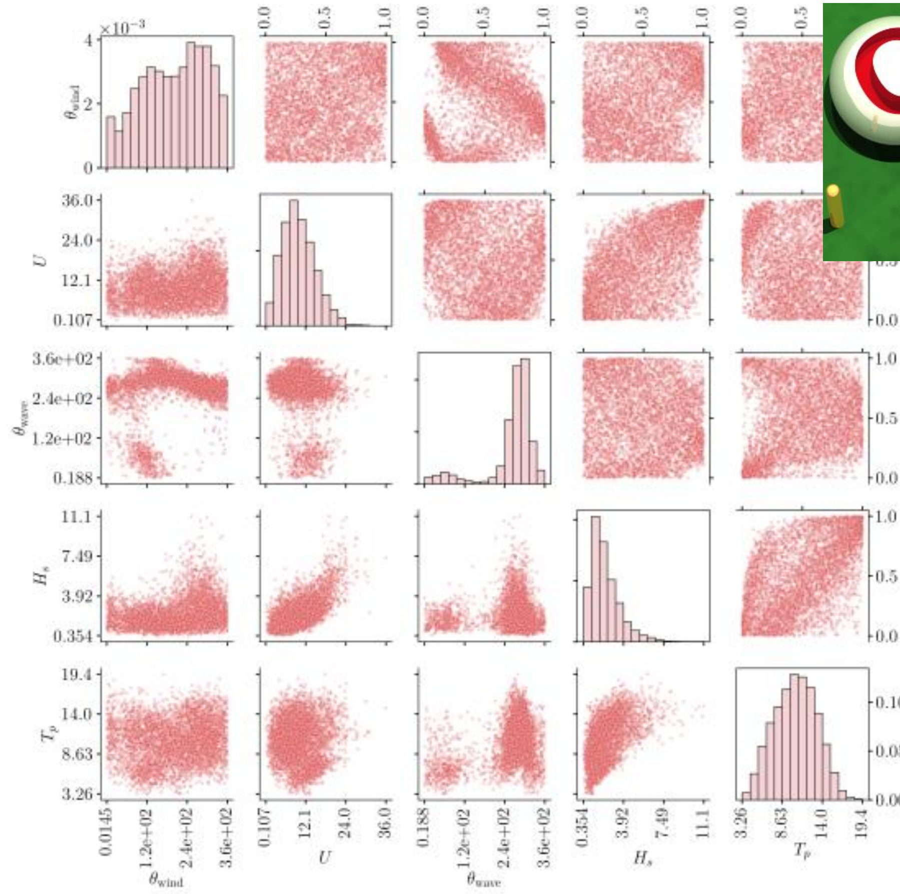
Name	*Notation*	*Fitted model*
Wind speed	U	Weibull $(\beta = 11.4, \alpha = 2.2, \gamma = 0)$
Wind direction	θ_{wind}	KDE
Significant wave height	H_s	Inverse Normal $(\mu = 2.3, \lambda = 6.8)$
Wave period	T_p	KDE
Wave direction	θ_{wave}	KDE

Table 1: Marginal inference results of the South Brittany metocean data.

- Hybrid inference of the South Brittany metocean conditions (size $n = 10^4$) [Vanem et al., 2023]



(a) South Brittany ANEMOC data ($n = 5000$).



(b) Monte Carlo sample ($n = 5000$) from the hybrid model (EBC with $\{m_j = 100\}_{j=1}^{d}$).

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Conclusion and questions

Main use-case challenges

- In situ metocean data distribution with a complex dependence
  - Large amounts of data
  - Nonparametric copulas offer an accurate goodness of fit
- Computationally relatively costly model ~40 min (CPU time) / evaluation
  - Requires wrapping 2 numerical models + computing mechanical post-processing
  - Performing the study on HPC allowed us to compute over 10^5 evaluations on the Teesside model
- Strongly nonlinear and skewed output variable of interest
  - Log transform of the output can help with the skewness

How to collaborate?

- Working on the Teesside model is a bad idea for two reasons
  - Confidentiality issues on metocean data and simulated results for an operating farm
  - In the wind turbine community, reference models have more impact (e.g., reference IEA15MW turbine)
- As usual, industrial cases are not "plug a play"