Probabilistic surrogates for floating wind-turbine load emulation

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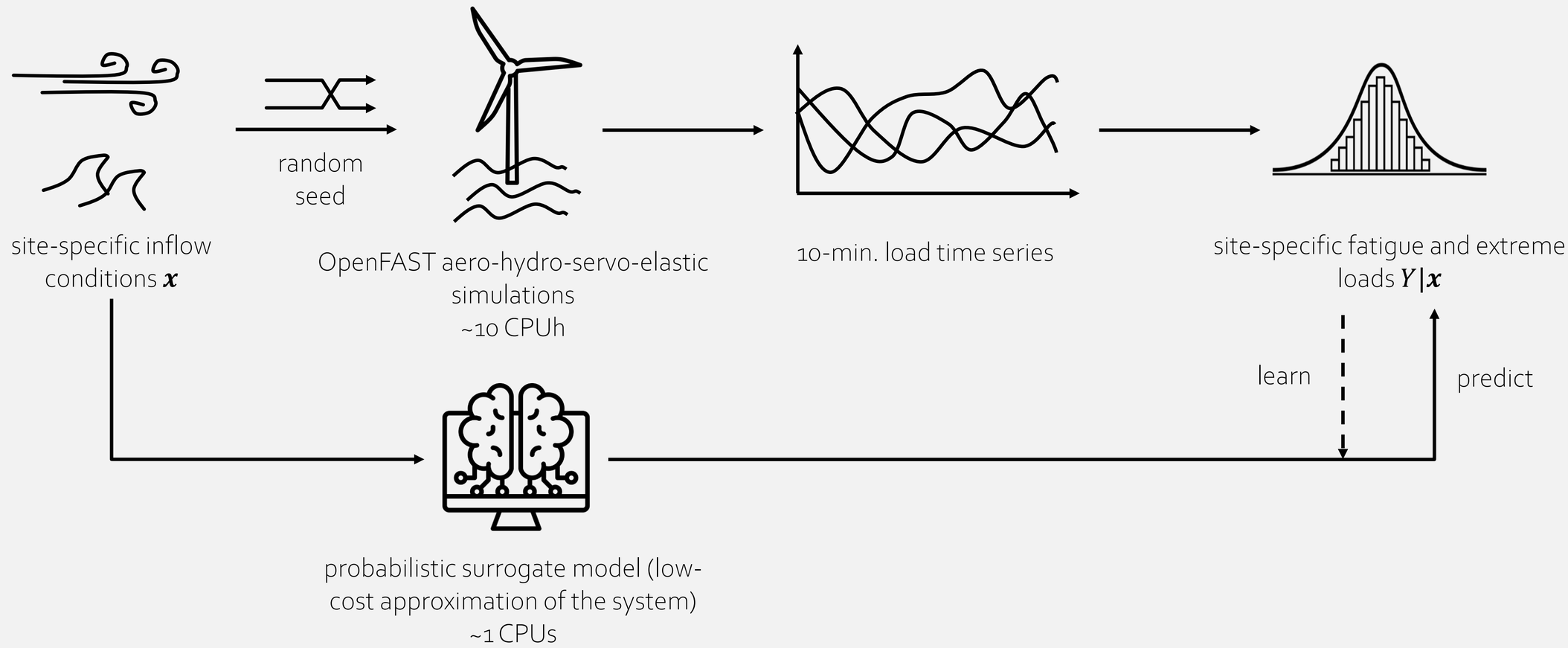
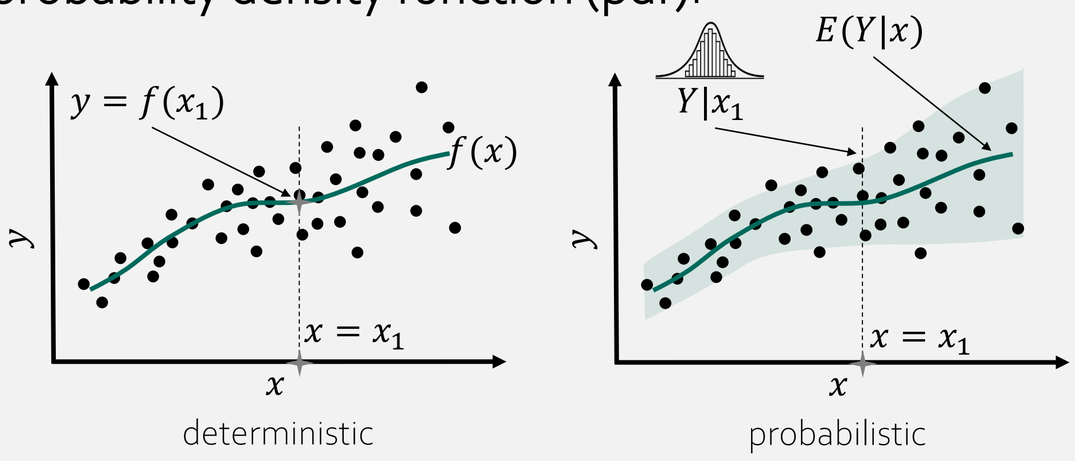
OUTLINE



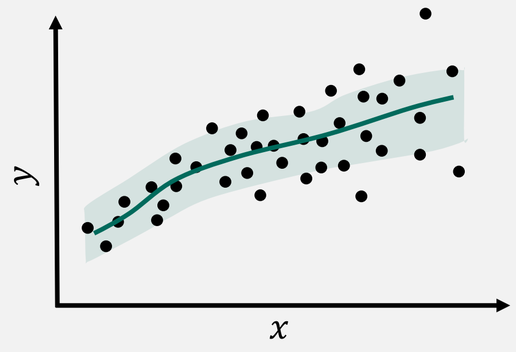
Icon credits to Insticon, KonKapp and Annette Spithoven from the Noun Project https://thenounproject.com/

APPROACH

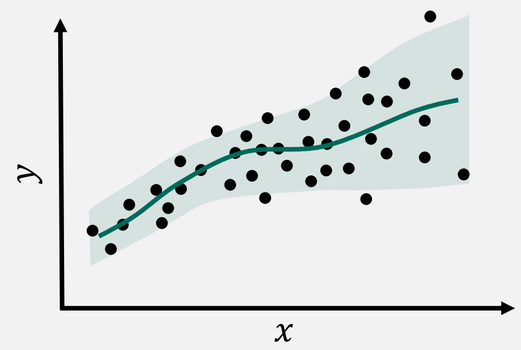
In measurements and in simulations, the wind turbine is subject to **randomly varying inflow conditions**. For a set of mean inflow conditions $\boldsymbol{x}$, **the loads are not deterministic, but random variables of unknown probability density function (pdf)**.



MODELS



Gaussian process regression (GPR)
$y_i = f(x_i) + \varepsilon$



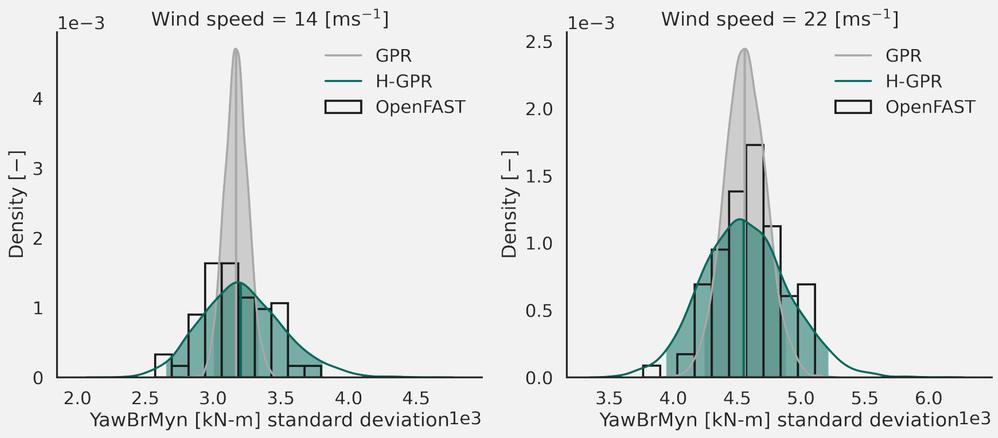
heteroscedastic Gaussian process regression (H-GPR)
$y_i = f(x_i) + \varepsilon(x_i)$

Bayesian statistical methods like the heteroscedastic Gaussian process regression can directly infer the underlying mean and variance of the pdf from a noisy database.

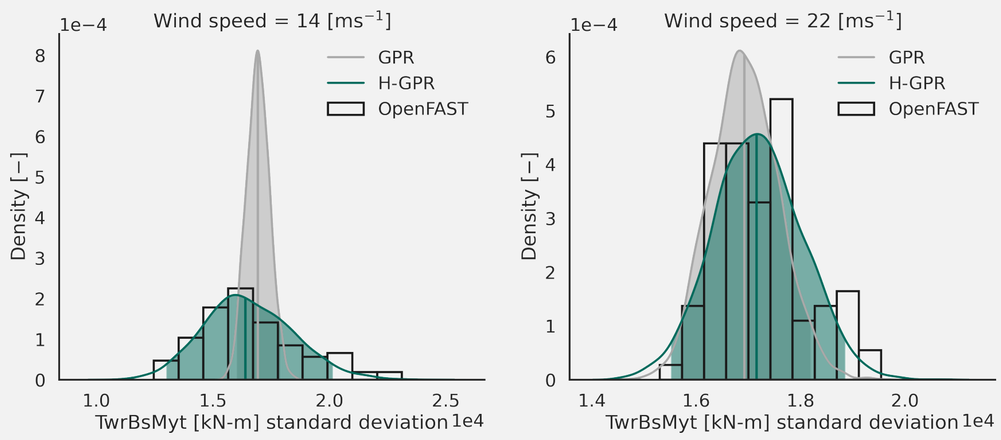
RESULTS

The predicted conditional pdf at specific values of $\boldsymbol{x}$ for a **fixed-bottom offshore wind turbine** are shown. **H-GPR shows a very good agreement with the full order model** and a significant improvement over the more commonly used GPR model. The work is currently being extended to floating wind turbines.

Tower top fore-aft moment (standard deviation)



Tower base fore-aft moment (standard deviation)



$\boldsymbol{x}$ = [wind speed ($\boldsymbol{u}$), turbulence intensity = $\frac{12(0.75u + 5.6)}{u}$, α = 0.08, significant wave height = $1\mathrm{m}$, wave period = $7\mathrm{s}$, wave direction = $0°$]$^{\mathrm{T}}$

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