Data-Driven Surrogate Models for (Floating) Offshore Wind Turbines

Deepali Singh

Richard P. Dwight, Laurent Beaudet, Kasper Laugesen, Paul Deglaire, Axelle Viré

Photo: Principle Power

STEP4WIND – Training network in floating wind energy

TU Delft

SIEMENS Gamesa RENEWABLE ENERGY

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Structure

- WHAT and WHY: FOWT design challenges
- HOW: machine learning framework and stochastic models

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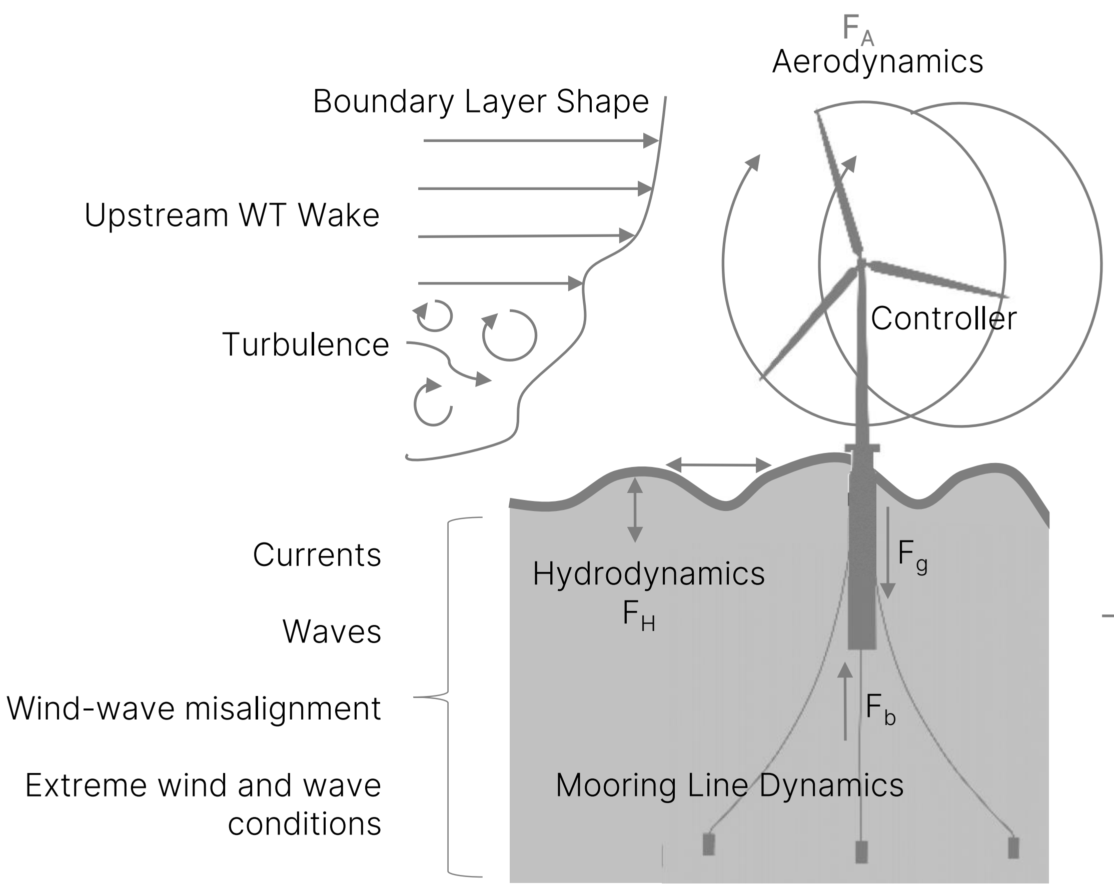
Wind Turbine Design Challenges



Design Situation	Wind Conditions	Wave	Wind Wave Directionality	Sea Currents	Water Level	Other Conditions
Power production						
Power production or occurrence of fault						
Start up						
Normal shut down						
Emergency shut down						
Parked						
Parked with fault						
Transport, assembly, maintenance						

Multi-dimensional probabilistic design space with ~1M *expensive* aero-servo-hydro-elastic simulations [1]

Ultimate, Extreme, Average and Fatigue Loads

Ref [1] IEC 61400-3

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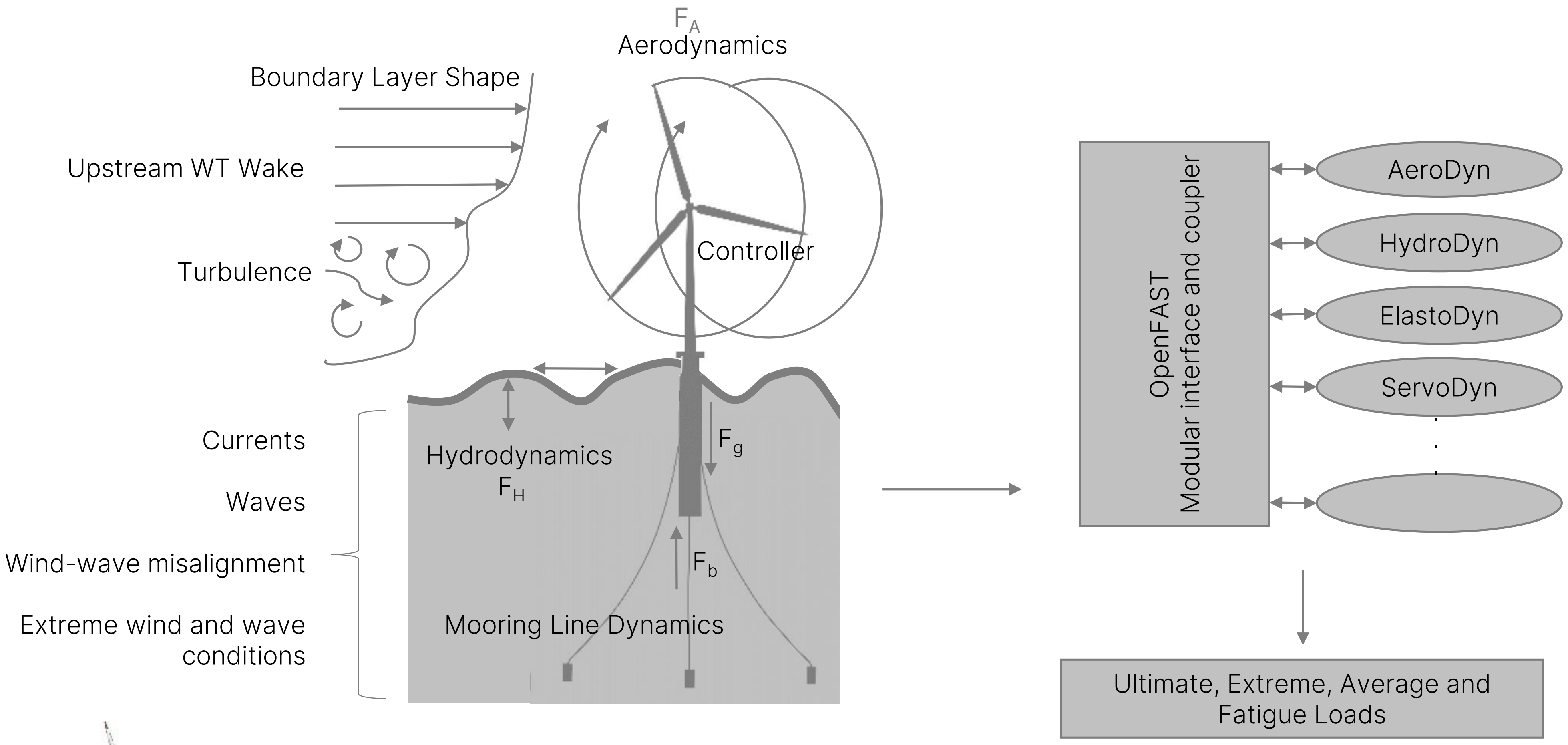
Wind Turbine Design Challenges



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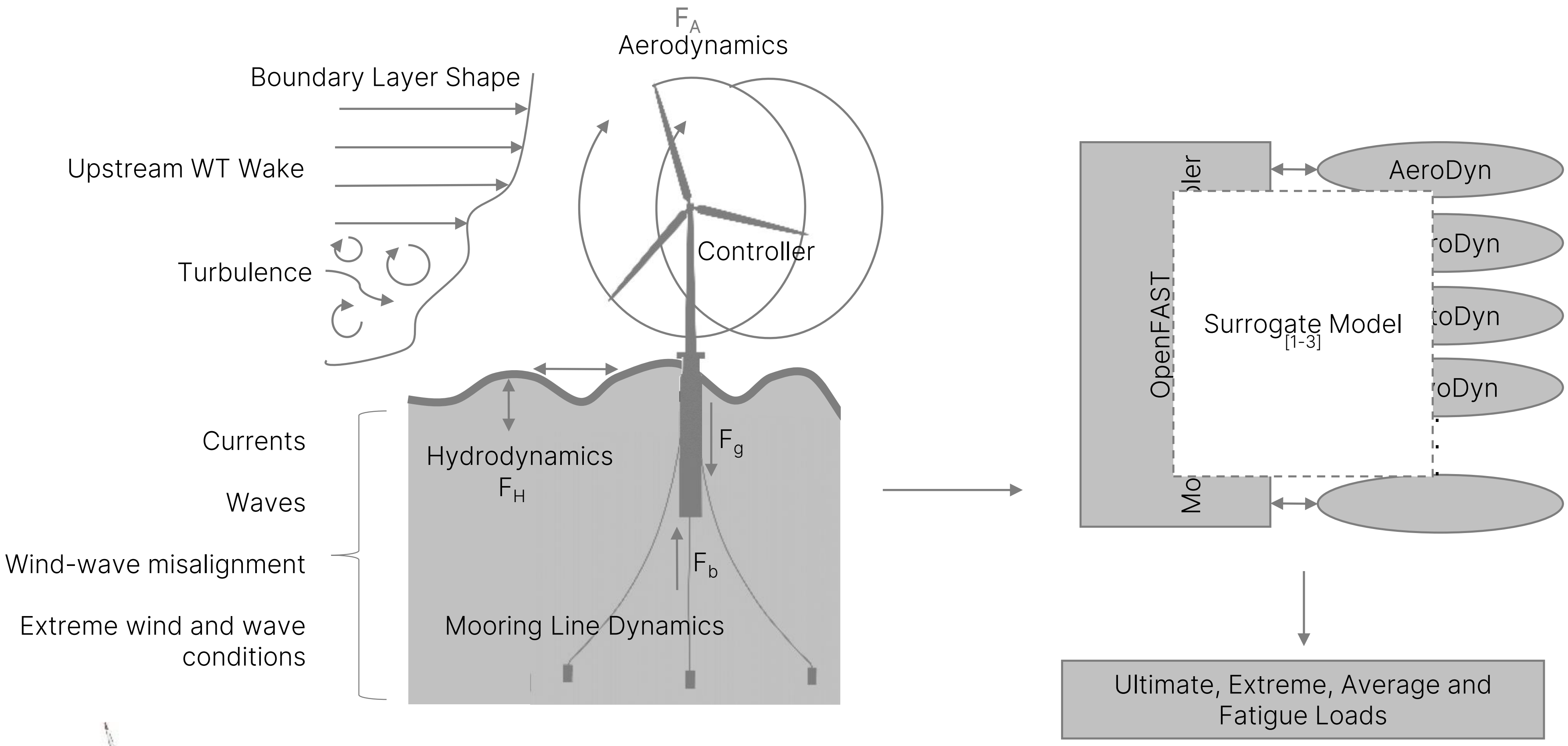
Proposed Solution



STEP4WIND

Ref [1] Dimitrov, N. K., Kelly, M., Vignaroli, A., Berg, J., From wind to loads: wind turbine site-specific load estimation with surrogate models trained on high-fidelity load databases (2018) Wind Energy Science

[2] Schröder, L., Dimitrov, N. K., Verelst, D. R., A surrogate model approach for associating wind farm load variations with turbine failures (2020) Wind Energy Science

[3] Zhu, X., Sudret, B. Global sensitivity analysis for stochastic simulators based on generalized lambda surrogate models (2021) Reliability Engineering & System Safety

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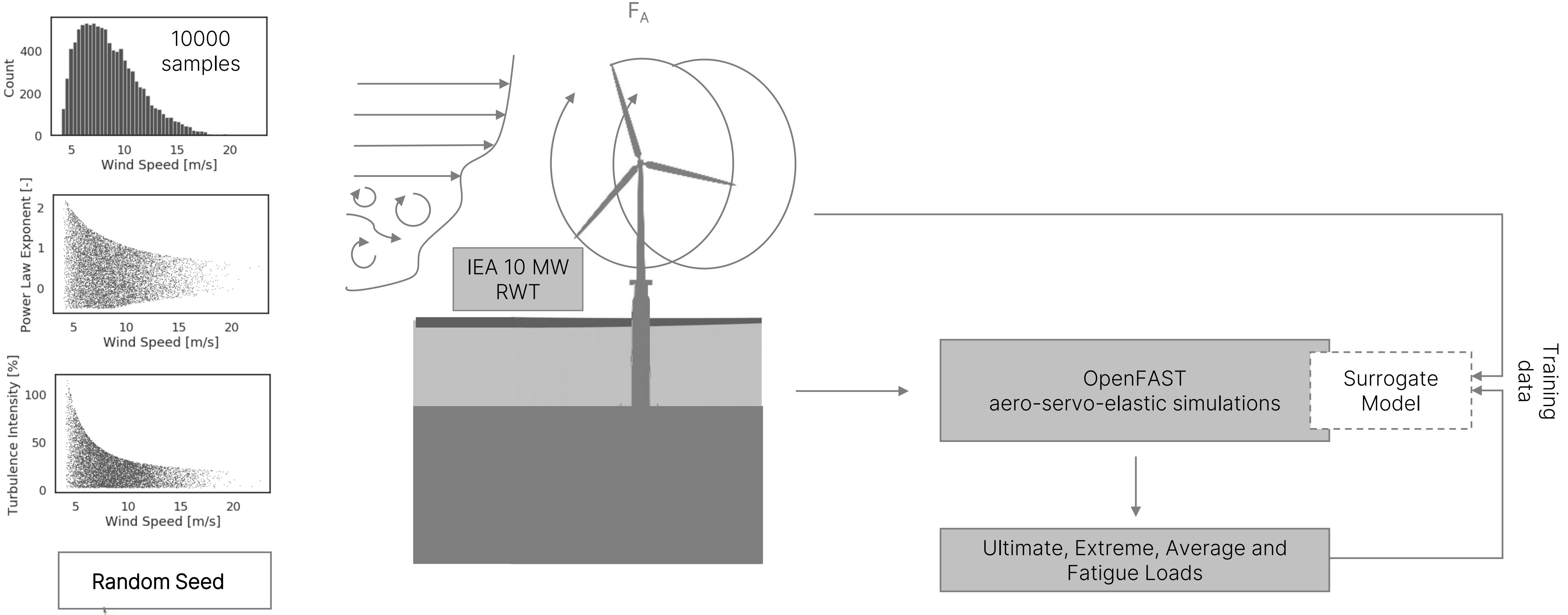
Machine Learning Framework



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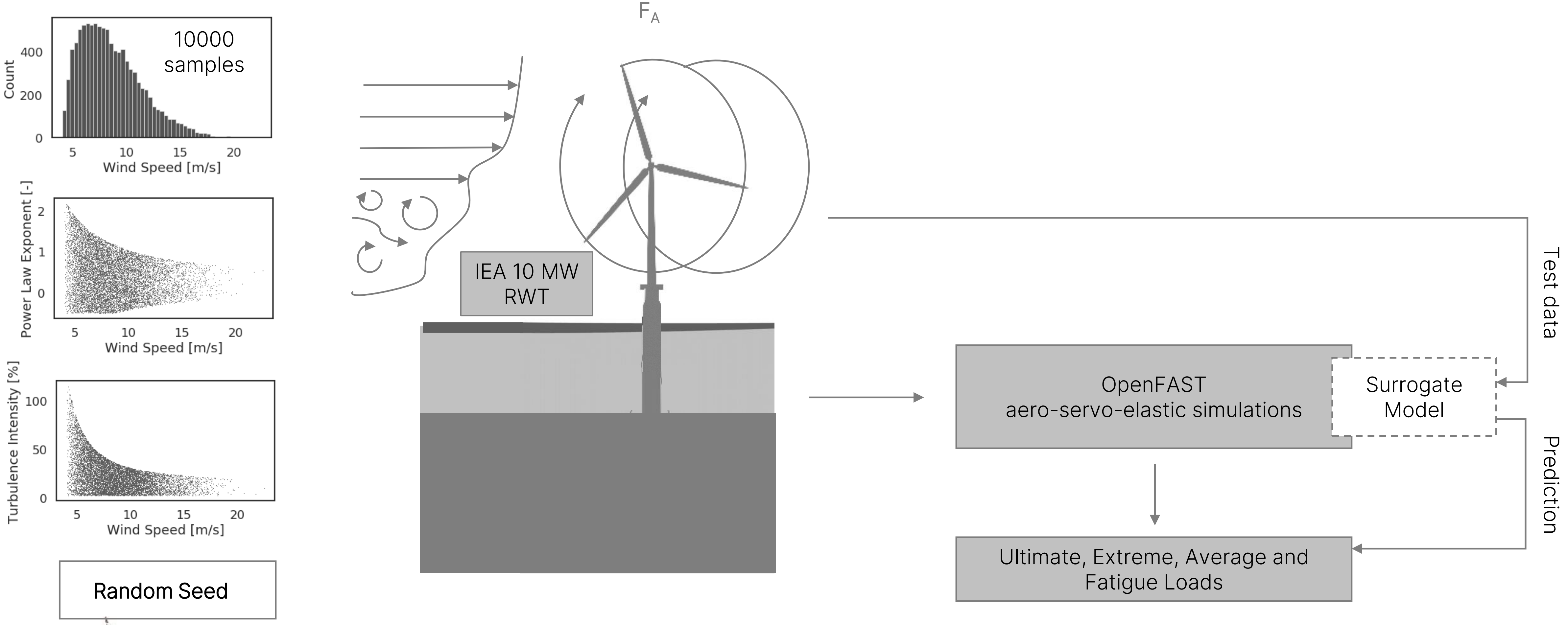
Machine Learning Framework



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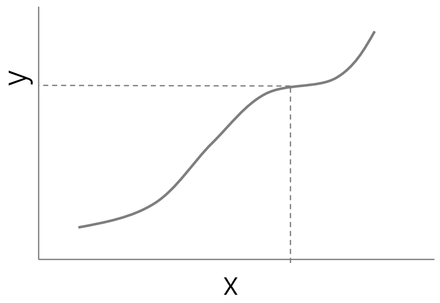
System Behaviour

Deterministic

$M_d: x \mapsto y$

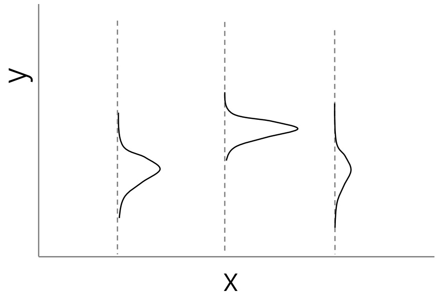


System

$D = \{(x_i, y_i) | i = 1, \dots, n\}$

Stochastic

$M_s: D_x \times \Omega \to \mathbb{R}$
$(x, z) \mapsto M_s(x, z)$ [1]



Ref [1] Zhu et. al., Replication-based emulation of the response distribution of stochastic simulators using generalized lambda distributions (2020) International Journal for Uncertainty Quantification

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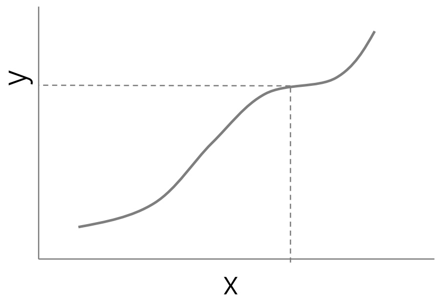

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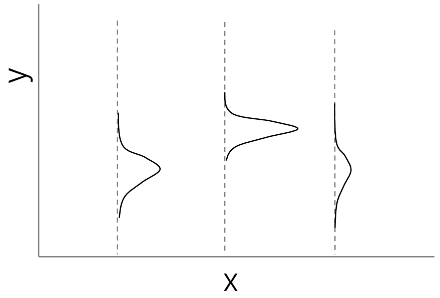

If $x = x_0$:

$$(Y | X = x_0) \equiv M_s(x_0, z)$$

If $z = z_0$:

$$x \mapsto M_s(x, z_0)$$

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Stochastic Models

Dataset $D = \{(x_i, y_i)|i = 1, \ldots, n\}$

- Gaussian Process Regression/ Kriging[1]

Gaussian process is a class of probability distribution over possible functions that fit a set of points, and represents prior knowledge about f

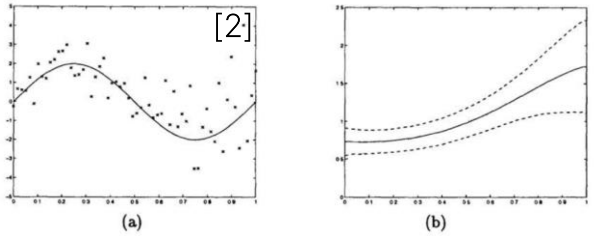
$$y_i = f(x_i) + \epsilon_i$$
$$\epsilon_i = N(0, \sigma^2)$$
$$cov(y_i, y_j) = \eta^2 \exp\left(-\frac{1}{2}\frac{|x_i - x_j|^2}{l^2}\right) + \sigma^2 \delta_{ij}$$
$$y|D = N(\hat{\mu}, \hat{\Sigma})$$

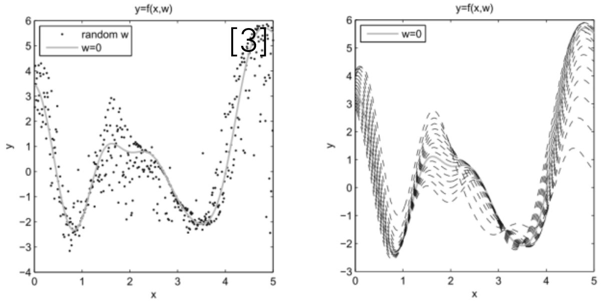
- Gaussian Process with a latent variance[2]

$$y_i = f(x_i) + \epsilon_i$$
$$z_i = \log\left(SD\left(\epsilon(x_i)\right)\right) = r(x_i) + J_i$$

- Gaussian Process with a latent covariate[3]

$$y_i = g(x_i, z_i) + \zeta_i$$
$$f(x) = \int g(x, z)p(z)dz$$
$$cov(y_i, y_j) = \eta^2 \exp\left(-\Sigma_{k=1}^{p} \frac{1}{2}\frac{|x_i - x_j|^2}{l_k^2} - \frac{(z_i - z_j)^2}{l_{p+1}^2}\right) + \sigma^2 \delta_{ij}$$





Ref [1] C. E. Rasmussen & C. K. I. Williams, Gaussian Processes for Machine Learning (2006) MIT Press. ISBN 026218253X
Useful: https://aerodynamics.lr.tudelft.nl/~rdwight/cfdiv/Videos/04/index.html
[2] Goldberg, P. W., Williams, C. K. I., Bishop, C. M., Regression with input dependent noise: A Gaussian process treatment (1998) Advances in neural information Processing Systems
[3] Wang, C., Neal, R., Gaussian Process Regression with Heteroscedastic or Non-Gaussian Residuals (2012) arXiv:1212.6246v1

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Stochastic Models

Dataset $D = \{(x_i, y_i)|i = 1, \dots, n\}$

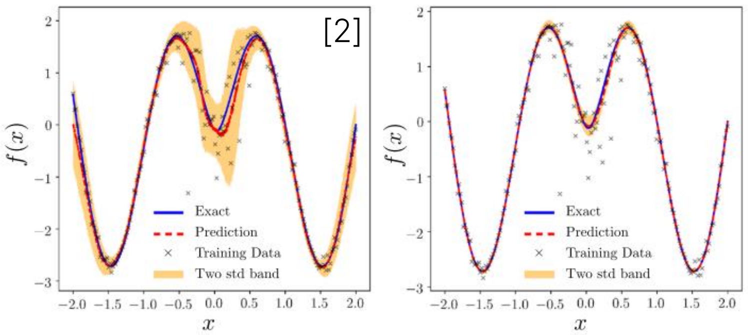
- Stochastic gradient variational Bayes[1]
- Conditional generative model[2]

$$y = f_\theta(x,z)$$
$$p(y|x) = \int p(y|x,z)\, p(z|x,y)\, dz$$

$p(y|x,z)$ parametrized to $p_\theta(y|x,z)$ -> decoder

$p(z|x,y)$ parametrized to $q_\phi(z|x,y)$ -> encoder

The model is trained by minimizing difference between the joint distribution of the generated data $p_\theta(x,y)$ and the joint distribution of the observed data $q(x,y)$



- Replication based models[3]
  - Regression performed over the parameters of a generalizable PDF
- Overview of other interesting methods: reference[4]

Ref [1] Kingma, D. P., Welling, M., Auto-encoding variational bayes (2014) 2nd International Conference on Learning Representations, Conference Track Proceedings
[2] Yang, Y., Perdikaris, P., Conditional deep surrogate models for stochastic, high-dimensional, and multi-fidelity systems (2019) Computational Mechanics
[3] Zhu, X., Sudret, B. Global sensitivity analysis for stochastic simulators based on generalized lambda surrogate models (2021) Reliability Engineering & System Safety
[4] Sudret, B. and Zhu, X., Surrogate models for stochastic simulators: an overview with a focus on generalized lambda models (2021) MascotNum Workshop on "Stochastic simulators" (online)

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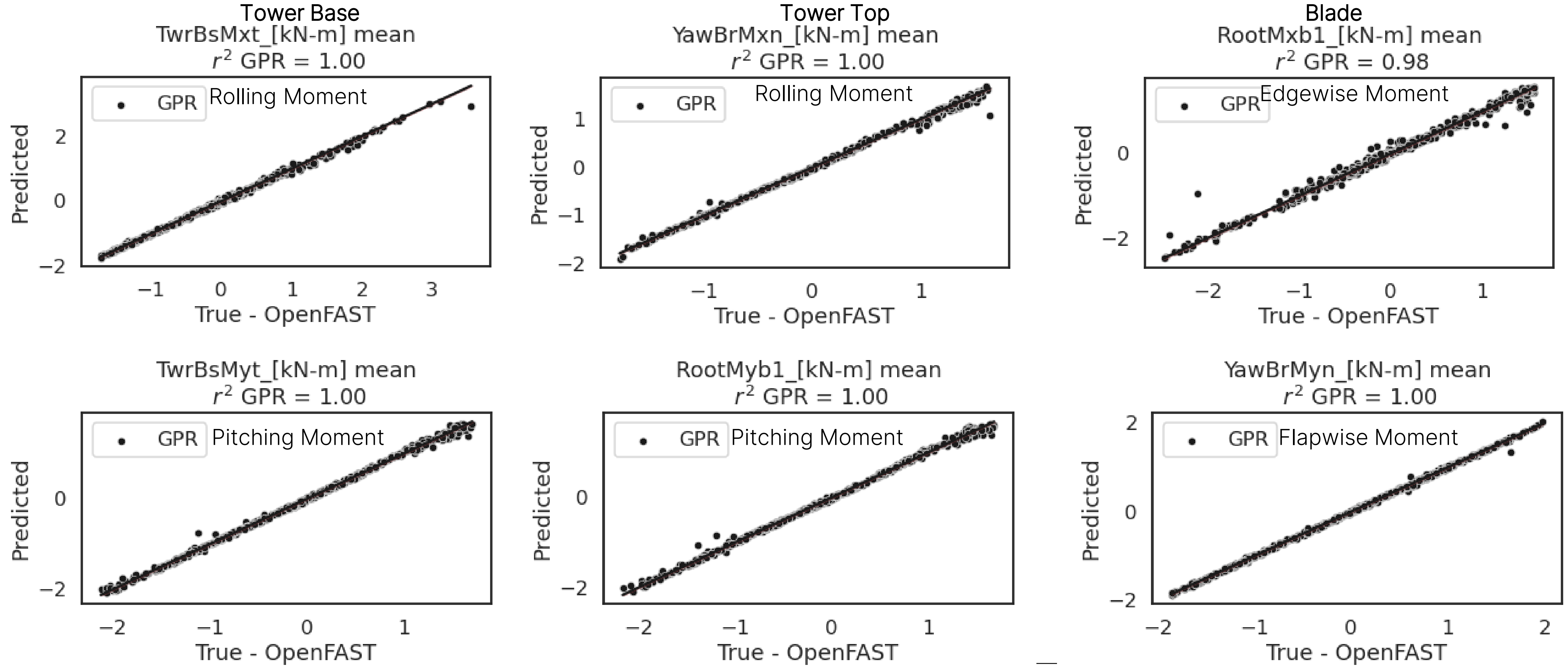
Results - averaged loads



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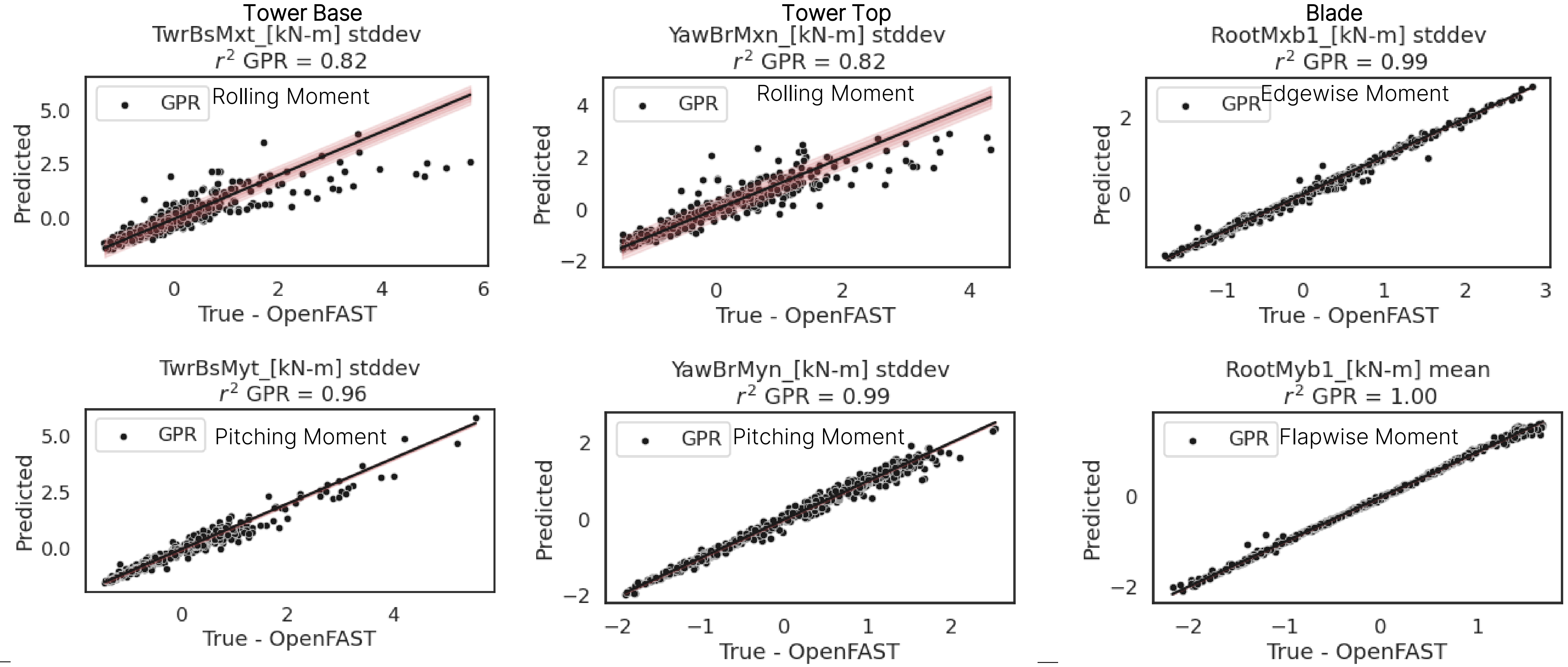
Results – stddev loads



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Questions

d.singh-1@tudelft.nl

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