# A NOVEL STRATEGY TO SURROGATE THE TRANSIENT RESPONSE OF WIND TURBINE SIMULATIONS

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## BACKGROUND

### The project

**HI**ghly advanced **P**robabilistic design and **E**nhanced **R**eliability methods for high-value, cost-efficient offshore **WIND**

- Cost reduction of offshore wind energy
- Safer and more reliable offshore wind turbines
- Improve wind turbine load predictions

### The Challenge

Find a surrogate $\widetilde{\mathcal{M}}$ for the *aero-servo-elastic* wind turbine simulator $\mathcal{M}$:

$$f(t) = \mathcal{M}(\boldsymbol{v}(\leq t)) \approx \widetilde{\mathcal{M}}(\boldsymbol{v}(\leq t))$$

- Response *time series* $f : \mathcal{T} \to \mathbb{R}$
- Discrete time axis $\mathcal{T} = \{0, 1, 2, \dots, N\}$
- Turbulent wind input $\boldsymbol{v} : \mathcal{T} \to \mathbb{R}^{\nu_w \times \nu_y \times \nu_z}$, $\boldsymbol{v}(\leq t)$: include wind speed history up to and including time $t$

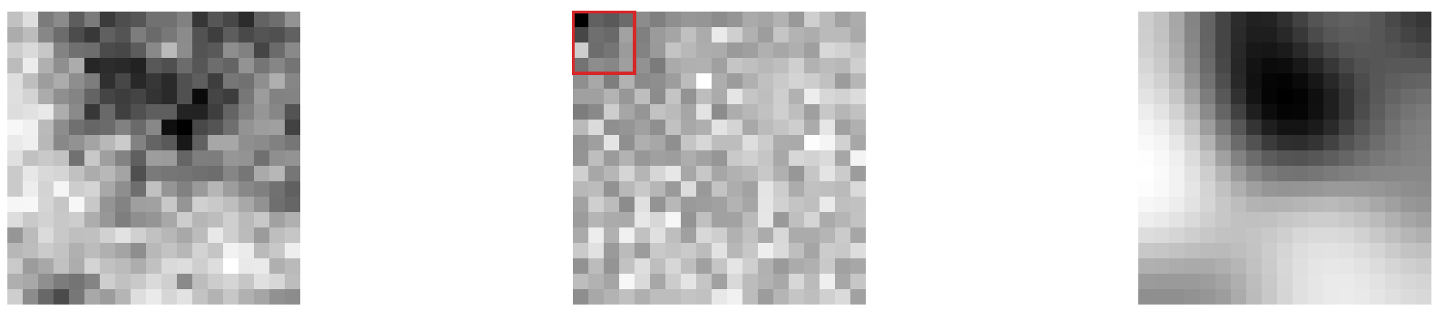
## STEP 1: SPATIAL DIMENSIONALITY REDUCTION

By construction, the longitudinal component of the wind speed, $\boldsymbol{v}_x(t)$, dominates. It is spatially coherent, while $\boldsymbol{v}_y(t)$ and $\boldsymbol{v}_z(t)$ are white noise.

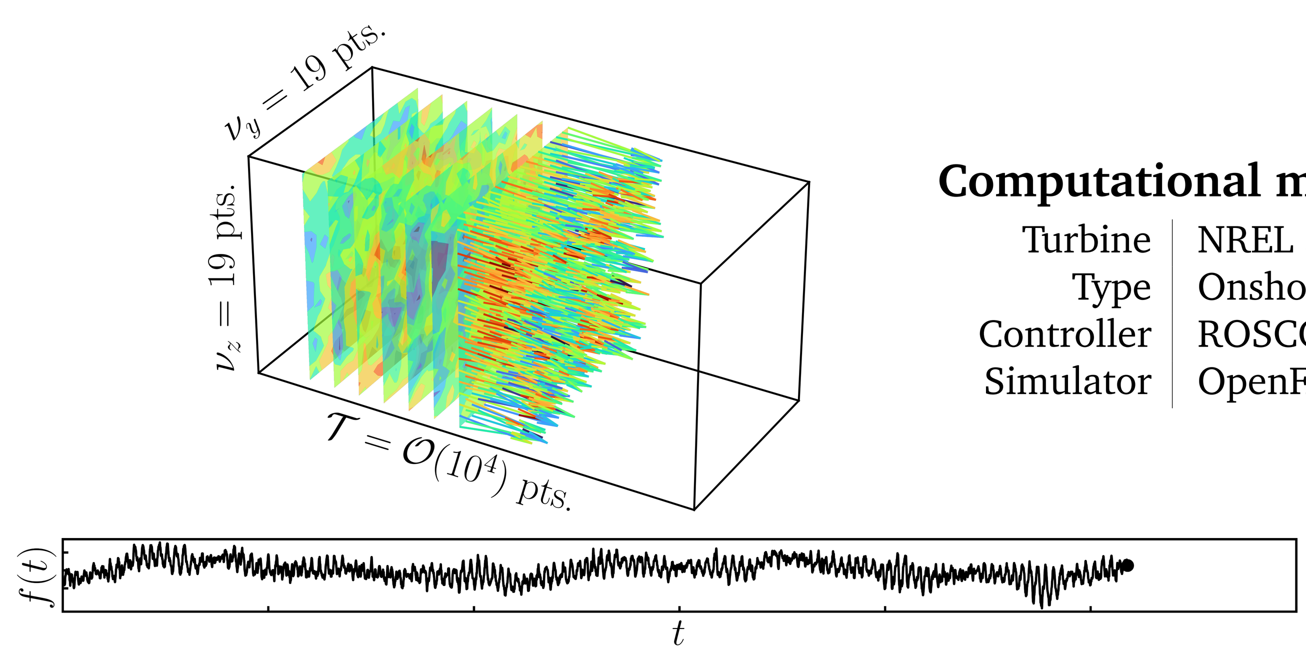
Project $\boldsymbol{v}_x(t)$ into its 2D discrete cosine transform coefficients $\boldsymbol{\xi}(t)$:

$$v_x^{\kappa\ell}(t) = \sum_{i=1}^{\nu_y} \sum_{j=1}^{\nu_z} \xi_{ij}(t) \cos\left[\frac{\pi}{\nu_y}\left(\kappa + \frac{1}{2}\right) i\right] \cos\left[\frac{\pi}{\nu_z}\left(\ell + \frac{1}{2}\right) j\right]$$

$\boldsymbol{v}_x(t)$ is well represented by a small subset of its spectral coefficients:

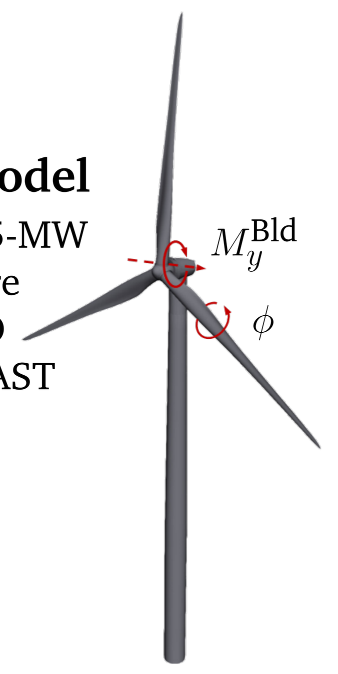


Original frame $\boldsymbol{v}_x(t=\tau)$ | Spectral coefficients $\log|\boldsymbol{\xi}(t=\tau)|$ | Reconstructed frame $\widetilde{\boldsymbol{v}}_x(t=\tau)$




**Computational model**

| | |
|---|---|
| Turbine | NREL 5-MW |
| Type | Onshore |
| Controller | ROSCO |
| Simulator | OpenFAST |

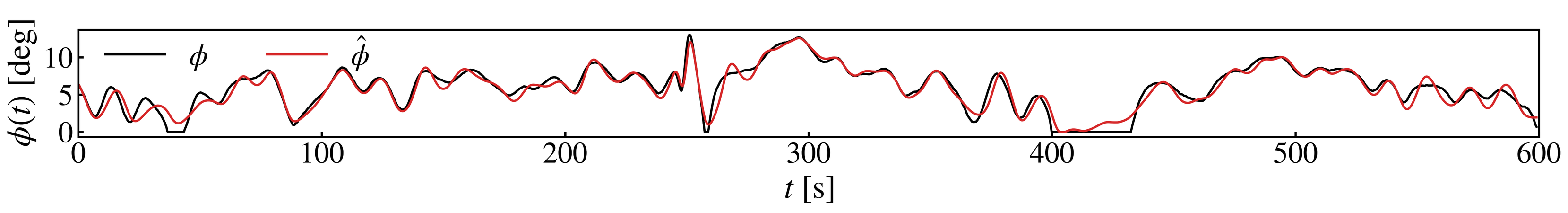



## STEP 2: CONTROL VARIABLES

To improve energy efficiency, wind turbines have a control system. Pitch control is particularly important because the pitch angle has a strong influence on wind-induced loads.

Emulate the pitch angle $\phi(t)$ with a polynomial *nonlinear autoregressive with exogenous input* (NARX) model $\widetilde{\mathcal{M}}^{\phi}$:

$$\hat{\phi}(t+\delta t) = \widetilde{\mathcal{M}}^{\phi}(\hat{\phi}(t), \hat{\phi}(t-l_1^{\phi}), \hat{\phi}(t-l_2^{\phi}), \dots, \hat{\phi}(t-l_{n_\phi}^{\phi}), \boldsymbol{\xi}(t+\delta t), \boldsymbol{\xi}(t), \boldsymbol{\xi}(t-l_1^{\xi}), \dots, \boldsymbol{\xi}(t-l_{n_\xi}^{\xi}))$$

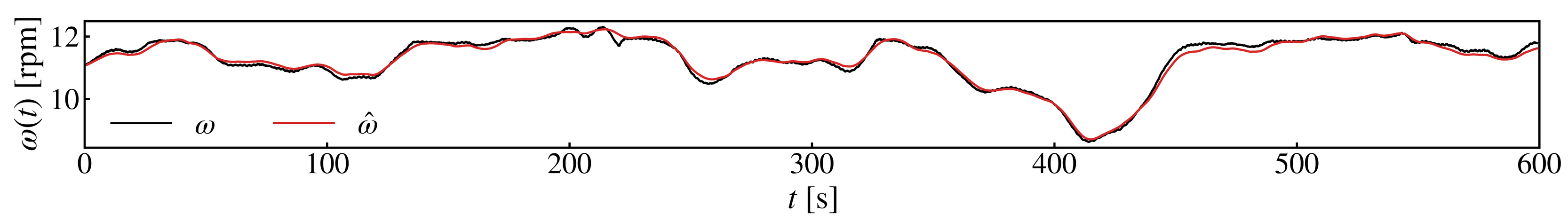



## STEP 3: AUXILIARY VARIABLES

Many response quantities of a wind turbine depend on its rotor orientation. E.g. blade loads depend on the position of the blades due to gravity and because wind speeds are generally higher at high altitudes.

Predict rotor speed, $\omega(t)$, as a function of the spectral coefficients, $\boldsymbol{\xi}(t)$, and the predicted blade pitch, $\hat{\phi}(t)$, using a polynomial NARX model $\widetilde{\mathcal{M}}^{\omega}$:

$$\hat{\omega}(t+\delta t) = \widetilde{\mathcal{M}}^{\omega}(\hat{\omega}(t), \hat{\omega}(t-l_1^{\omega}), \hat{\omega}(t-l_2^{\omega}), \dots, \hat{\omega}(t-l_{n_\omega}^{\omega}), \hat{\boldsymbol{\phi}}(t+\delta t), \hat{\boldsymbol{\phi}}(t), \hat{\boldsymbol{\phi}}(t-l_1^{\phi}), \dots, \hat{\boldsymbol{\phi}}(t-l_{n_\phi}^{\phi}), \boldsymbol{\xi}(t+\delta t), \boldsymbol{\xi}(t), \boldsymbol{\xi}(t-l_1^{\xi}), \dots, \boldsymbol{\xi}(t-l_{n_\xi}^{\xi}))$$




Reconstruct the rotor azimuth, $\theta(t)$, from the predicted rotor speed. Subsequently, construct an input manifold $\boldsymbol{\zeta}(t) = \{\boldsymbol{\xi}(t), \hat{\phi}(t), \hat{\boldsymbol{z}}(t)\}$:

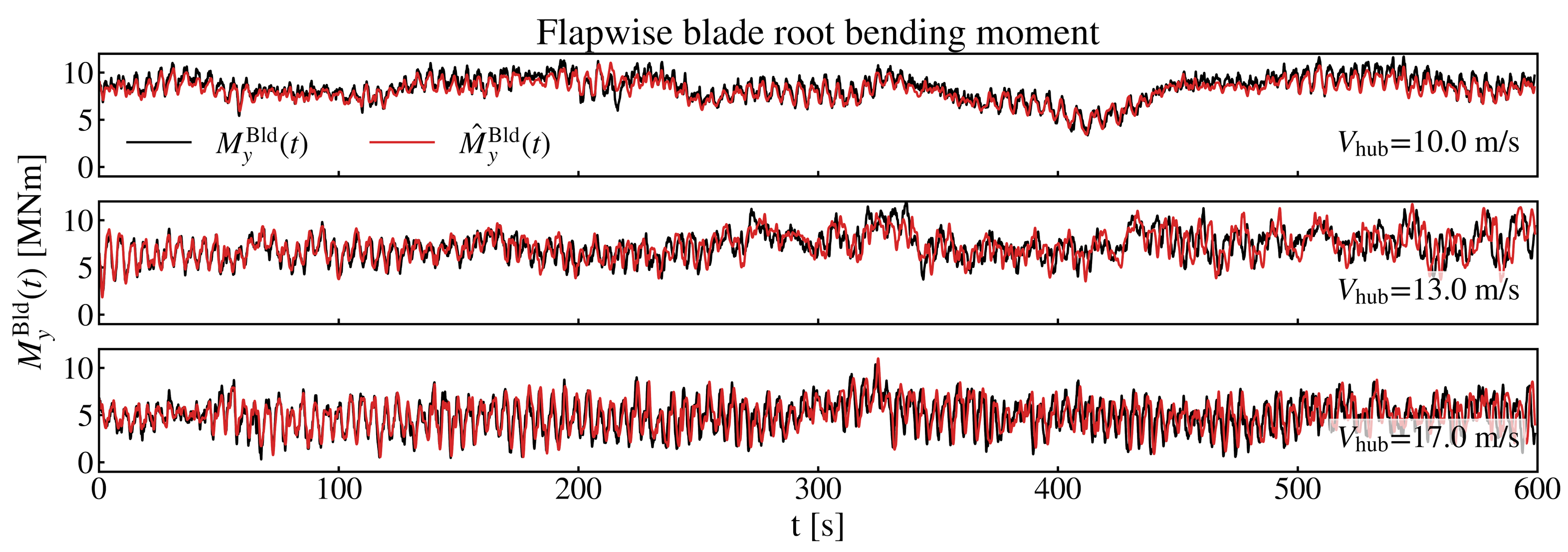
- $\hat{\boldsymbol{z}}(t)$ contains physically meaningful features
- E.g. higher frequency harmonics: $\hat{z}_1(t) = \cos 3\hat{\theta}(t)$ and $\hat{z}_2(t) = \sin 3\hat{\theta}(t)$

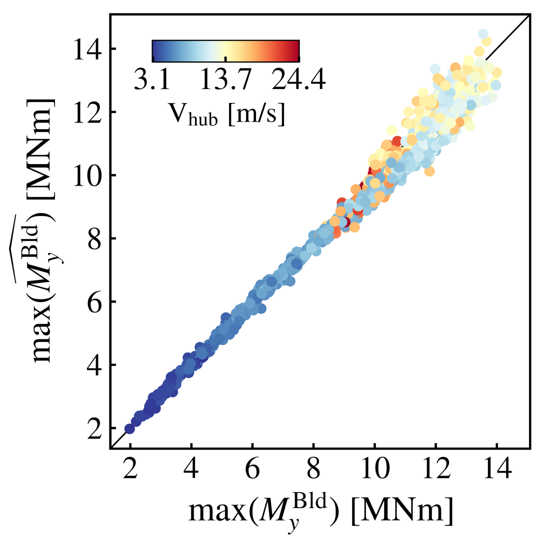
## STEP 4: QUANTITY OF INTEREST

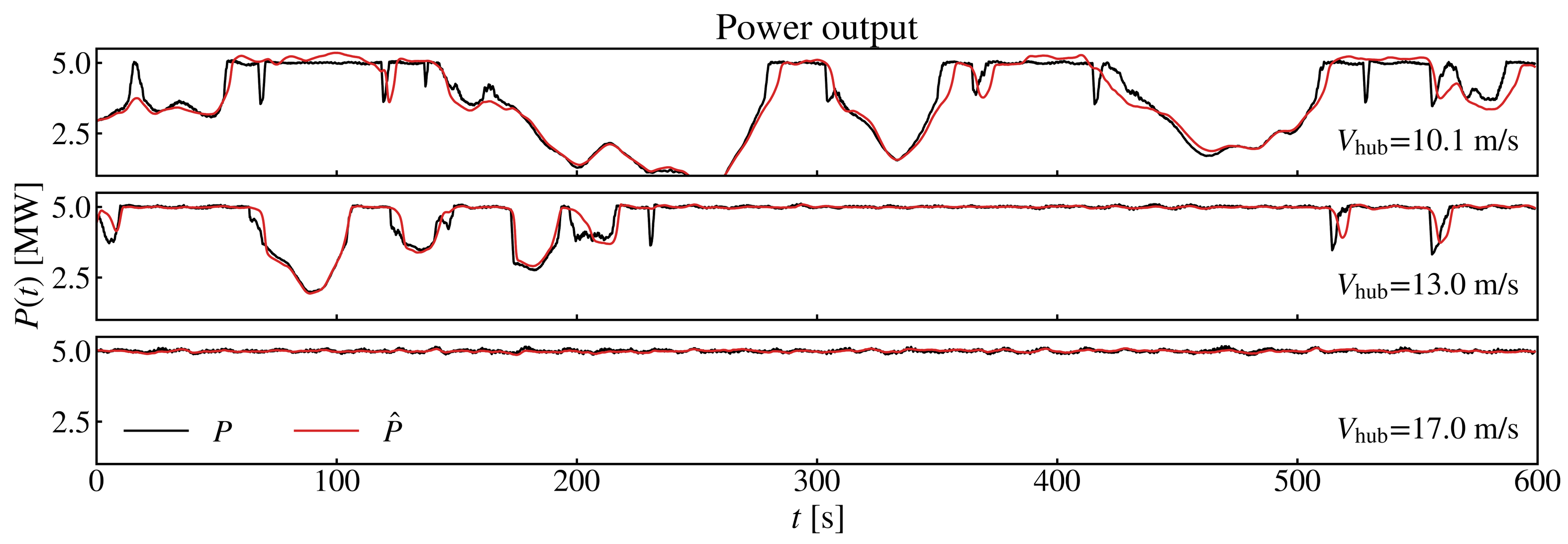
Predict the quantity of interest, $y(t)$, as a function of $\boldsymbol{\zeta}(t)$:

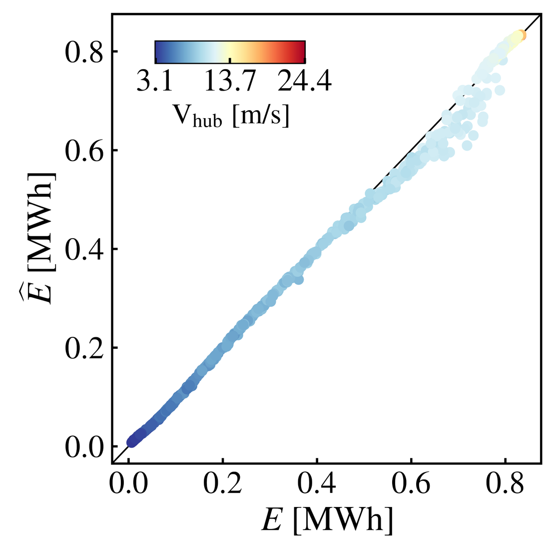
$$\hat{y}(t+\delta t) = \widetilde{\mathcal{M}}(\hat{y}(t), \hat{y}(t-l_1^{y}), \hat{y}(t-l_2^{y}), \dots, \hat{y}(t-l_{n_y}^{y}), \boldsymbol{\zeta}(t+\delta t), \boldsymbol{\zeta}(t), \boldsymbol{\zeta}(t-l_1^{\zeta}), \dots, \boldsymbol{\zeta}(t-l_{n_\zeta}^{\zeta}))$$

- Flapwise blade root moment $M_y^{\text{Bld}}$
- Power output $P$ and produced energy $E$
- Mean wind speed at the hub $V_{\text{hub}}$
- Out-of-sample results




### Conclusion

- Multistep approach performs highly nonlinear transform from input turbulence box to transient response
- Fast to construct and to evaluate polynomial models provide good accuracy
- Trained only on $\mathcal{O}(10^2)$ 10-min simulations

### Outlook

- Automate construction of surrogate
- Application to offshore wind turbine case study

Risk, Safety & Uncertainty Quantification

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