From high-fidelity physics-based wind plant models to efficient reliability-based turbine design: How do we quantify the uncertainties?

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Uncertainty in Standards

From **Turbine-Level** Focus ...

- Class definitions (ref wind speed, turbulence category)
- Safety Factors, Characteristic Values
- Site Suitability

... to **Plant-Level** Design/Operation/Optimization

- Extensions: wind shear, stability, turbulence in specs/classes
- Interactions, wakes (in class definitions?)
- Need for improved design/simulation tools
- Safety factors w/ consideration for robustness & risks
- Economics; not too onerous; more validation studies

Uncertainty

Uncertainties are ubiquitous!

Site → atmosphere/ocean variables/processes

Turbine → models/dynamics/control/aero/structural/materials

Plant → interaction/wakes

Design → codifying a reliability rationale in standards

What are its various forms?

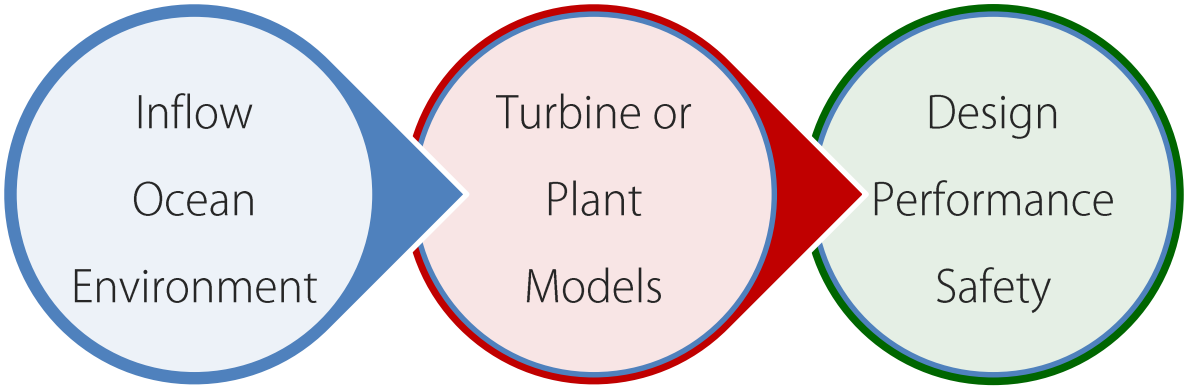
How can we account for it?

What approaches have been taken to quantify uncertainties, reduce risks, maintain target reliabilities?

Dealing with Uncertainty

Uncertainty Quantification

1. Uncertainty Propagation



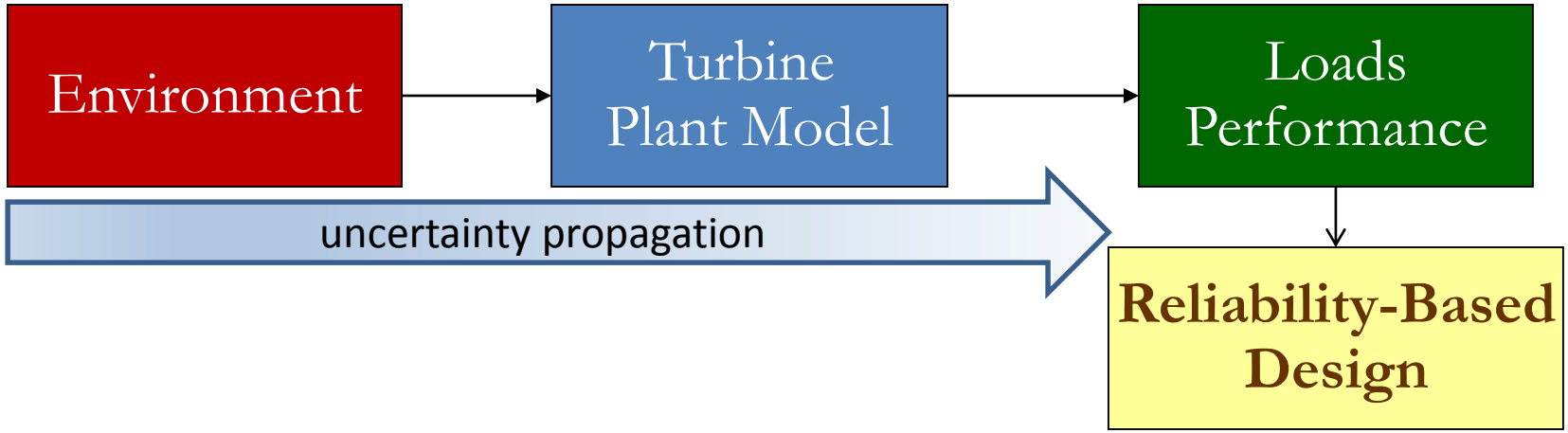
2. Validation and Verification of Models (Physics)

High-Dimensional (Random) Variable/Process Space

→ Low-Dimensional Surrogates;
Need for Efficiency; High-Performance Computing

Uncertainty Propagation

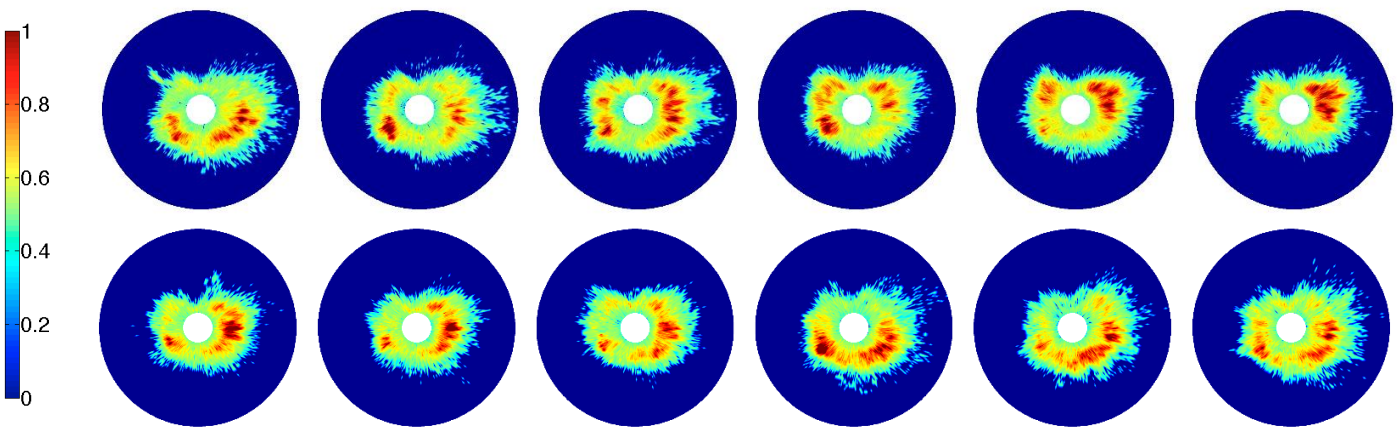
- We'll examine this in steps ...
- Probabilistic design ← Uncertainty (aleatory, epistemic)
  - from the environment/inflow/metocean
  - from models for simulation (aeroelastic, wakes, etc.)
- Act I ... from inflow (environment) to loads (plant performance)
- Act II ... from simulated loads to design practice/standards



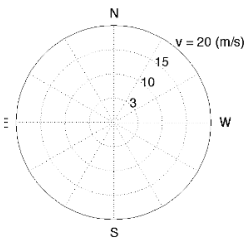
Uncertainty – Some Examples

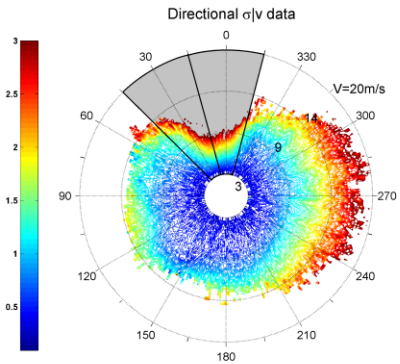
- Site assessment – extreme turbulence (field data)
- Site-specific challenges – offshore (field data)
- Uncertainty: Inflow → turbine loads (stochastic simulation)
- Stochastic wake (LES + reduced-order model)
- Extreme Loads (I-FORM, Extrapolation, etc.)
- Standards: Load Uncertainty (Practical Issues, HPC, etc.)
- UQ: Surrogates for Extremes (Validation, Propagation, PCE)
- *Extra Slides (if time permits)
  - Extreme Event Uncertainties – Downbursts, Hurricanes

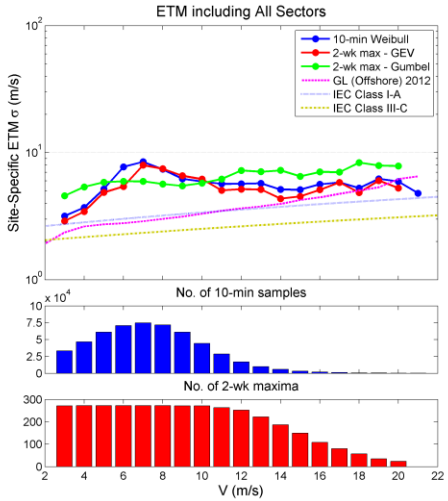
Site Assessment



std dev σ variation with V (monthly variation) at a site in Hamburg



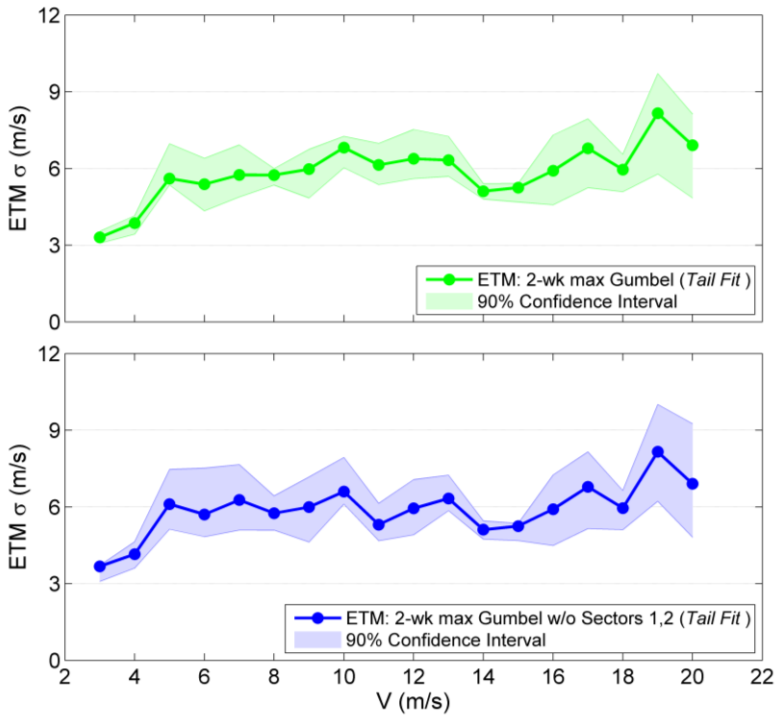


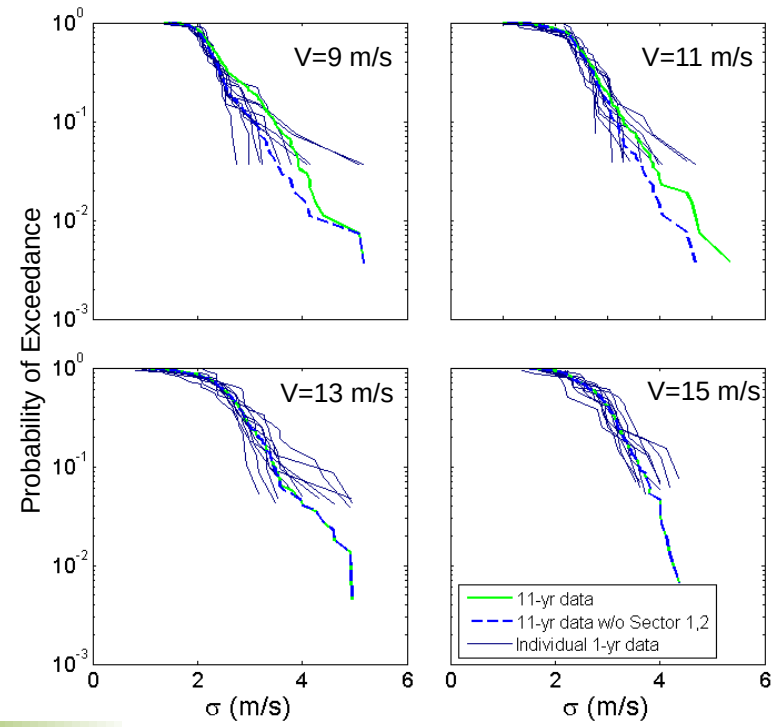


Topics of investigation in this study

- How do site-specific ETM levels compare with IEC class-based ETM definitions and GL (2012) offshore project certification approach?
- How does terrain complexity influence ETM levels?
- For wakes, ETM variation with direction is of interest
- ETM predictions based on measurement campaigns
- Quantification of ETM uncertainty due to sample size

Site Assessment



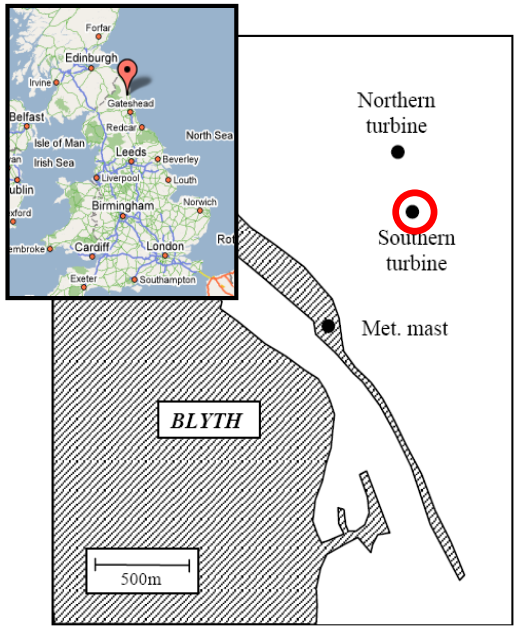


ETM Uncertainty: Illustration with Hamburg site

- ETM 90% confidence intervals show some variation with wind speed
- Considerable amount of uncertainty results from smaller sample size (1 year) vs. larger (11 years)
- At high wind speeds (greater than ~15 m/s), fewer data lead to larger confidence intervals (uncertainty)

Ref: Moon et al, JSEE, 2014. (http://dx.doi.org/10.1115/1.4028721)

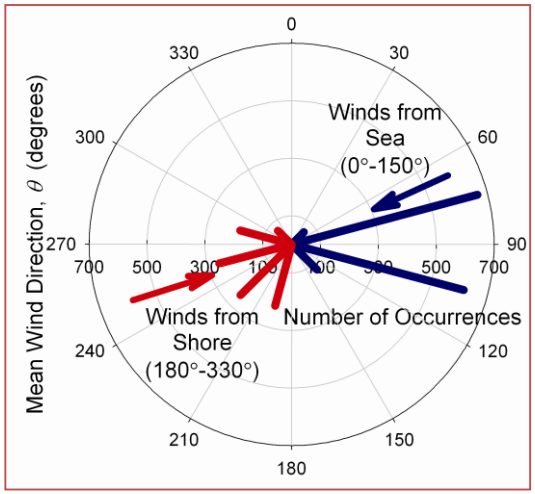
Site-Specific Challenges



Winds from the sea occur more often than winds from the shore.

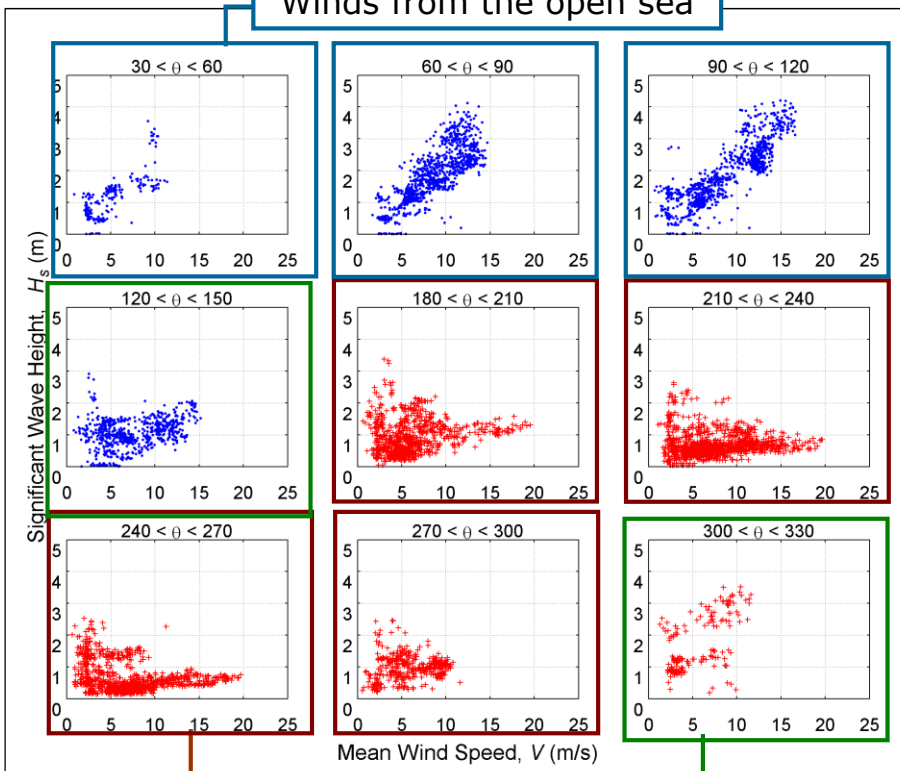
Data were very limited in many bins.

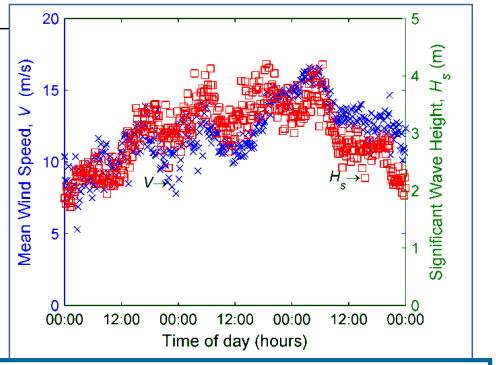
- 2MW Vestas V66
  - Hub height: 62 m
  - Blade diameter: 66 m
  - Average water depth: 9 m
- Measurements
  - Summary data: 10-min stats
  - Campaign data: time histories
- Load of interest
  - Mudline bending moment



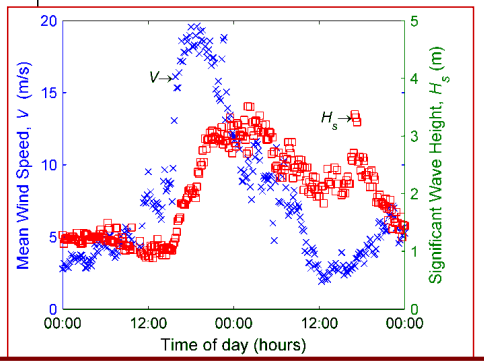
Site-Specific Challenges

Winds from the open sea

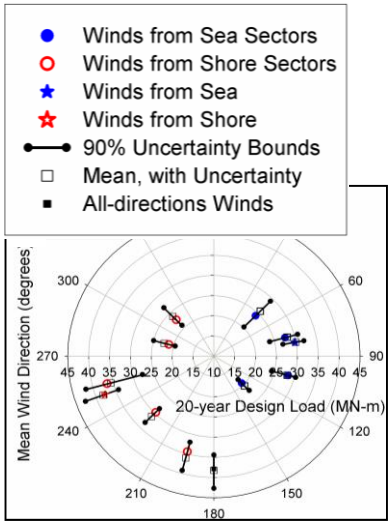




A storm for winds from sea



A storm for winds from shore



- A case for simulation models
- Avoids data scarcity issues.
- Lower costs
- But need validation of models

Winds from over land

Winds parallel to the shore

Ref: Agarwal and Manuel, JOMAE, 2008 (doi:10.1115/1.2827937)

Uncertainty: Inflow → Loads

- Uncertainties propagate from Inflow to Loads

Inflow Parameters → Turbulence Spectra → Inflow Fields → Turbine Loads

Solari & Piccardo (2001) – extensive database

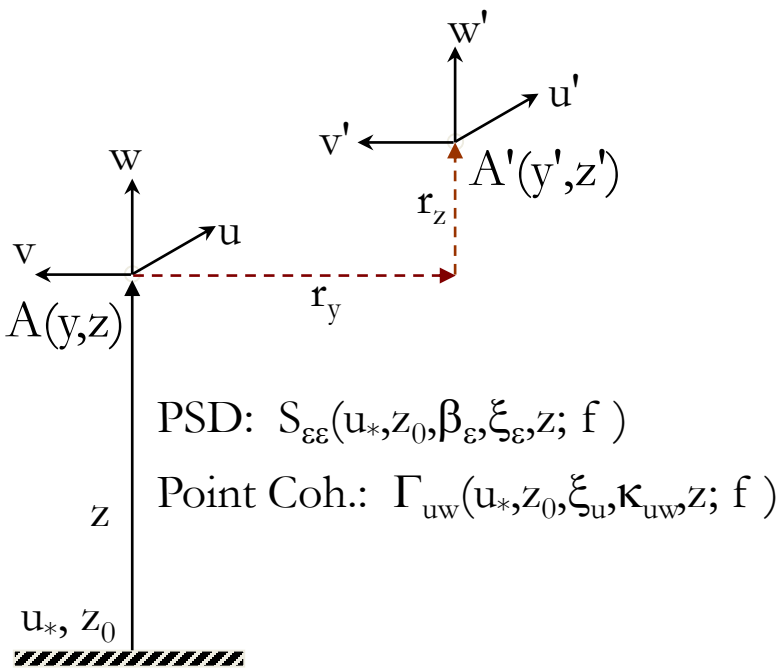
- A step-by-step investigation of the uncertainties
  - Generate inflow parameters → β_ε, ξ_ε, κ_{uw}, $C_{r\varepsilon}$
  - Compute turbulence spectra → $S_{\varepsilon\varepsilon}(z;f)$, $\Gamma_{uw}(z;f)$, $\Omega_{\varepsilon\varepsilon}(A,A';f)$
  - Inflow field simulations → $V_u(y,z;t)$, $V_v(y,z;t)$, $V_w(y,z;t)$
  - Turbine simulations → Turbine Loads

Uncertainty: Inflow → Loads

2 Fixed: z_0, u_*

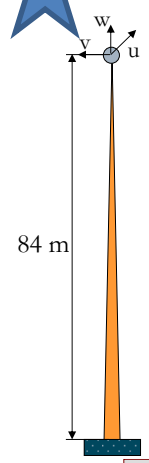
16 Random: β_ε, ξ_ε, κ_{uw}, $C_{r\varepsilon}$

(ε=u,v,w, r=r_x,r_y,r_z)

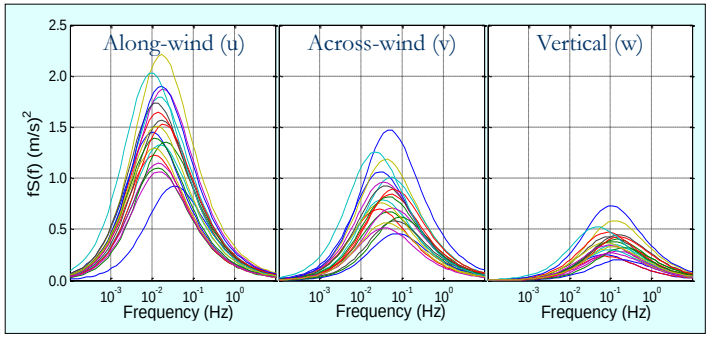


PSD: $S_{\varepsilon\varepsilon}(u_*,z_0,\beta_\varepsilon,\xi_\varepsilon,z;\ f)$

Point Coh.: $\Gamma_{uw}(u_*,z_0,\xi_u,\kappa_{uw},z;\ f)$



- 20 sets of Power Spectral Density (PSD) Functions (assume z = 84 m, z_0 = 0.05 m, u_* = 1.0 m/s)



Specify Fixed Inputs

z_0 and u_*

Generate realizations of inflow parameters

$\beta_u, \beta_v, \beta_w$ + ξ_u, ξ_v, ξ_w + κ_{uw} + C_{xu}, C_{xv}, C_{xw} C_{yu}, C_{yv}, C_{yw} C_{zu}, C_{zv}, C_{zw}

Statistics of Generated Inflow Parameters

Stats	β_u	β_v	β_w	ζ_u	ζ_v	ζ_w	κ_{uw}	C_{yu}	C_{yv}	C_{yw}
Mean	6.92	3.87	1.76	0.98	0.25	0.10	2.41	9.95	6.44	6.42
COV (%)	22.8	31.4	33.4	25.9	35.8	38.7	26.0	40.4	59.1	37.4

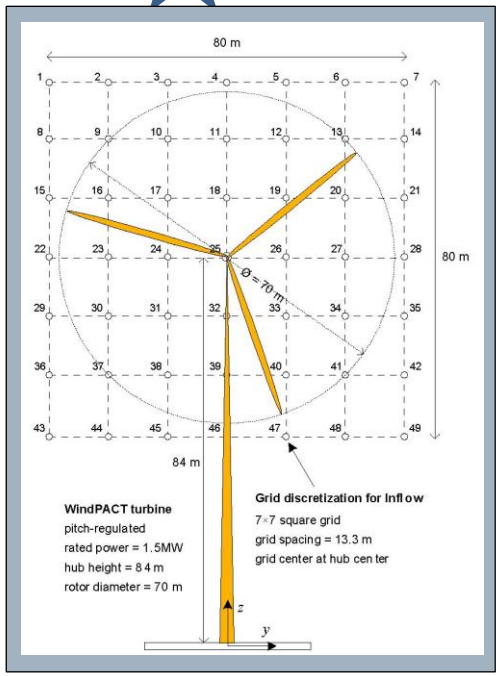
Examples: Range of β_u = [4.3,10.2]; Range of C_{yu} = [3.7,20.0]

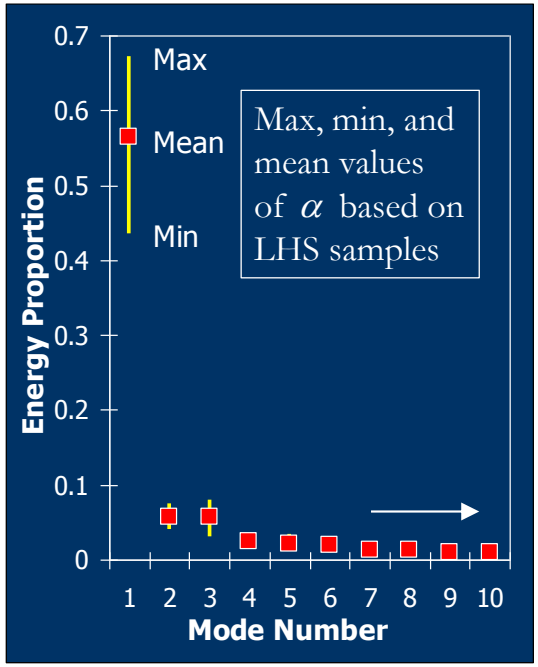
Uncertainty: Inflow → Loads

How much variability in the inflow propagates to turbine loads?

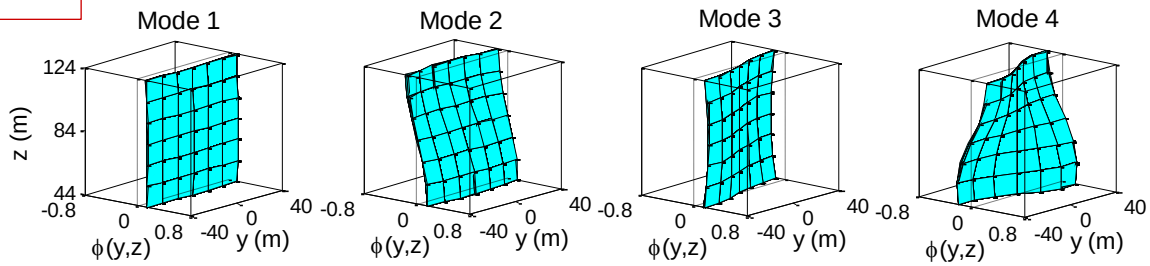
Case Study

- Wind Turbine
  - 1.5MW WindPACT virtual turbine
  - Statistics of BBM, TBM, and YM (blade, tower, and yaw moments)
- Inflow Field
  - Turbulence model of Solari & Piccardo
  - Veers' simulation approach
  - Simulated on a 7×7 square grid
- Simulations
  - Fifteen 10-minute simulations for each of twenty inflow parameter sets
  - Total of 300 inflow/turbine simulations





First 4 POD eigenmodes →



Uncertainty: Inflow → Loads

Stats	β_u	ζ_u	κ_{uw}	C_{yu}
Range	4.3-10.2	0.4-1.5	1.5-3.4	3.7-20
Mean	6.92	0.98	2.41	9.95
COV (%)	22.8	25.9	26.0	40.4

← Inflow

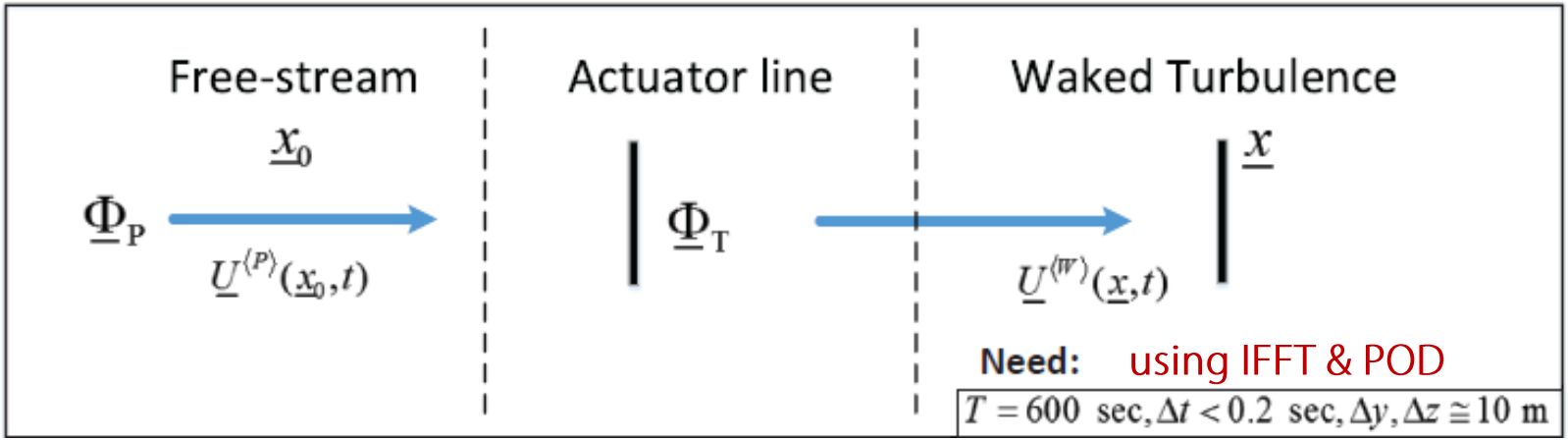
Loads ↓ (variability is actually lower than inflow)

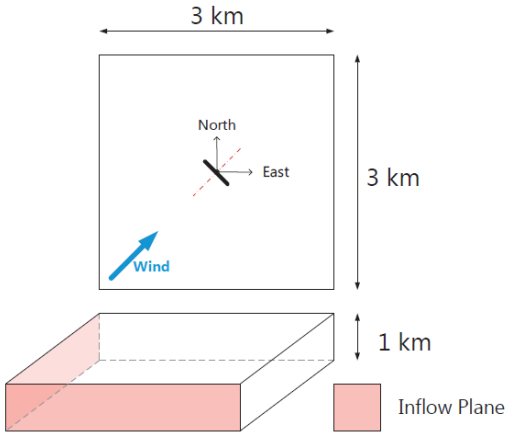
Stats	RMS (kN-m)			10-min Extreme (kN-m)		
	Blade moment	Tower moment	Yaw moment	Blade moment	Tower moment	Yaw moment
Range	562-589	8,030-8,181	196-297	1,142-1,422	13,056-15,923	736-1,161
Mean	573	8,094	240	1,268	14,633	894
COV (%)	1.2	0.6	12.7	6.8	6.5	13.4

Uncertainty propagation – not so bad in this case! ☺

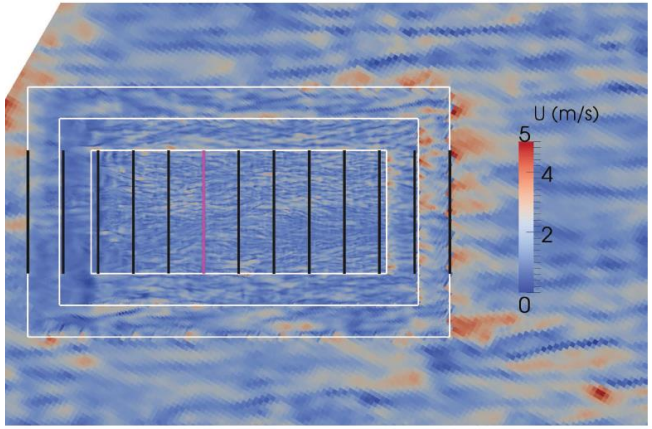
K. Saranyasoontorn and L. Manuel, JWEIA, 2008 (doi:10.1016/j.jweia.2008.01.005)

Stochastic Wake

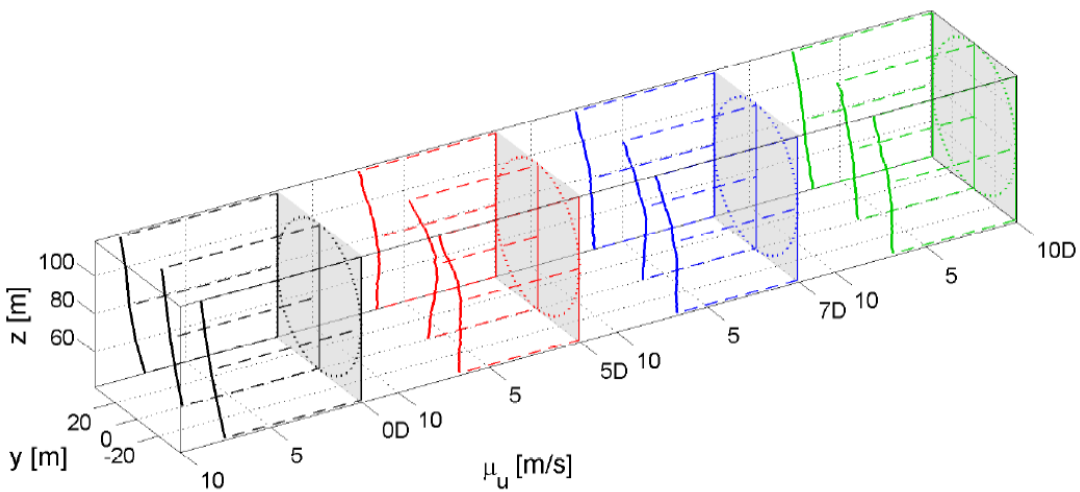




- Neutral BL
  8 m/s @ 80 m AGL
- Pot. temp 300 K
  unif up to 700 m;
  then linear var.
- Coriolis 30 deg N
- Quasi-equilibrium
  ~18,000 s.
- 1.5 MW turbine

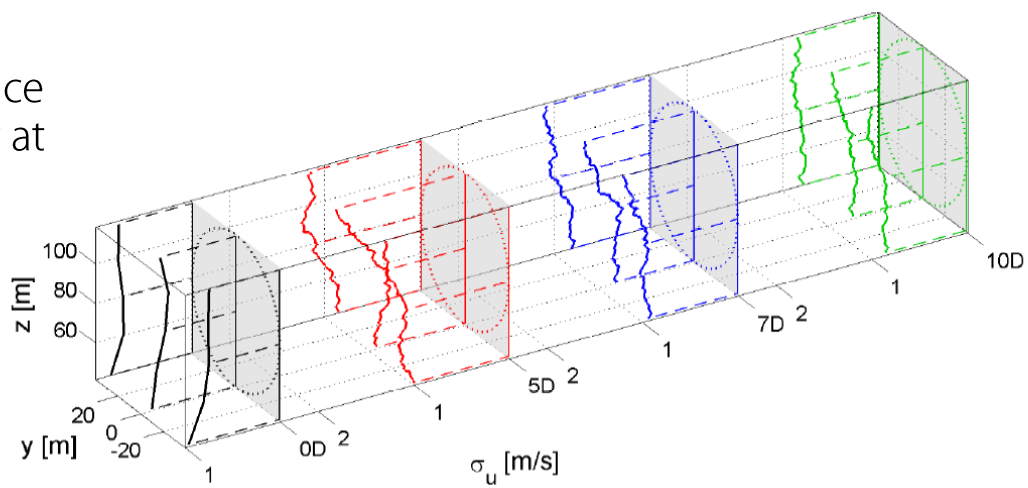


Stochastic Wake



- Estimate stochastic spectral or POD parameters from LES free-stream and waked wind fields
- Represent parameters using MMLR (multivariate multiple linear regression) for mean wind field (shear) and turbulence spectral models
- Compare loads from stochastic wake to ones from LES wake

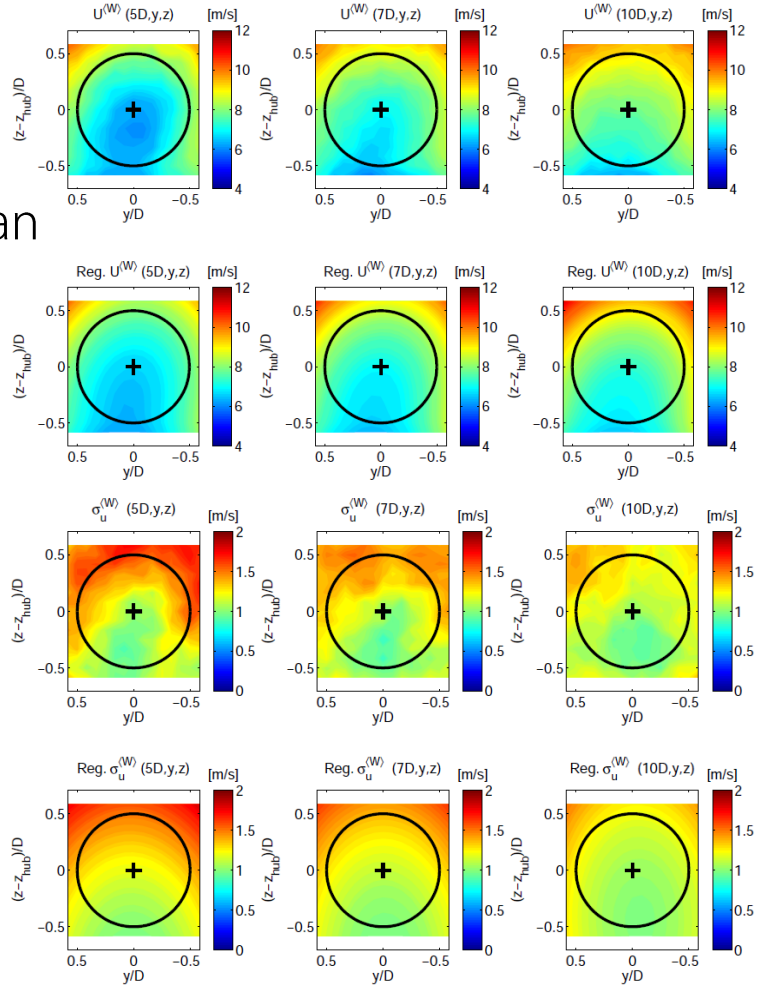
Mean wind speed deficit and turbulence increase in wake and gradual recovery at planes downwind are shown.



Ref: Moon et al, NREL Report, 2016 (draft)

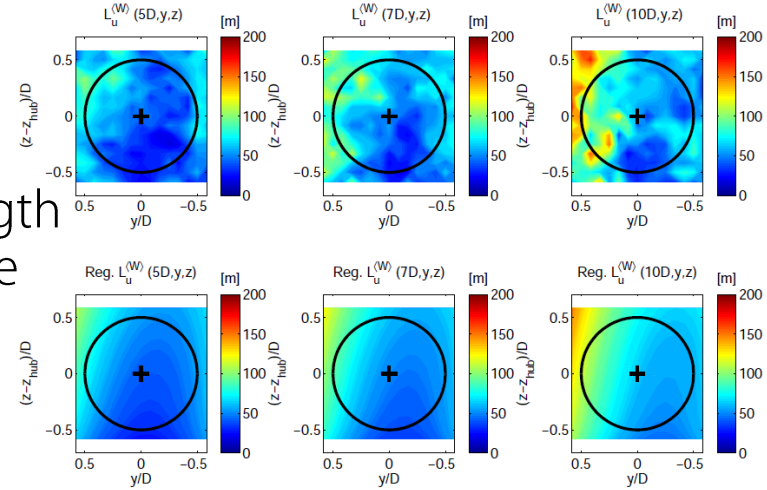
Stochastic Wake

Mean

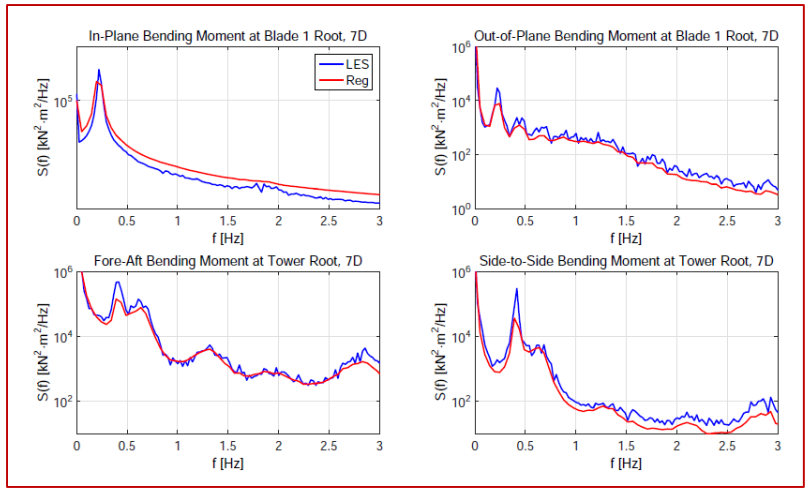


SD

Length Scale



Load PSD



"Extreme" Loads

- The 50-year load: l_{50} for any load measure, L
- How to derive it?

$$P(L > l_{50}) = \frac{1}{50 \times 365.25 \times 24} = 2.28 \times 10^{-6} \text{ (in 1 hour)}$$

- What is needed?
  Assume two variables for the "environment"—i.e., V and H_s

$$P(L > l) = \iint_{all(V,H_s)} \underbrace{P(L > l|V,H_s)}_{\text{load simulations}} \underbrace{f_{V,H_s}(v,h)}_{\text{environment}} dvdh$$

- The limit state function and "inverse" reliability
  (i.e., design, not analysis)

$$g(V,H_s,L;l_{50}) = l_{50} - L = l_{50} - L(V,H_s)$$

"Extreme" Loads

- So… $P[g(\mathbf{X}) < 0] = 2.28 \times 10^{-6} \rightarrow \beta = 4.58$; $\mathbf{X} \equiv \{V, H_s, L\}$
- β = target reliability index $\boxed{u_1^2 + u_2^2 + u_3^2 = \beta^2}$

environment

$$1 - p_1 = \Phi(u_1) = F_V(v)$$

$$1 - p_2 = \Phi(u_2) = F_{H_s|V}(h_s|v)$$

load simulations

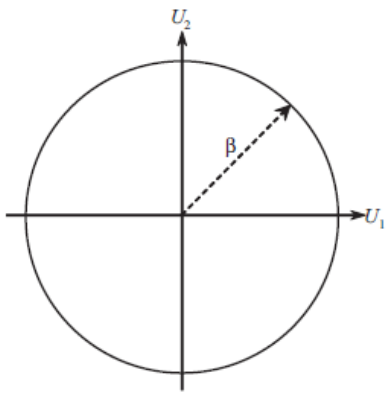
$$1 - p_3 = \Phi(u_3) = F_{L|V,H_s}(l|v,h) = 1 - G_{L|V,H_s}(l|v,h)$$

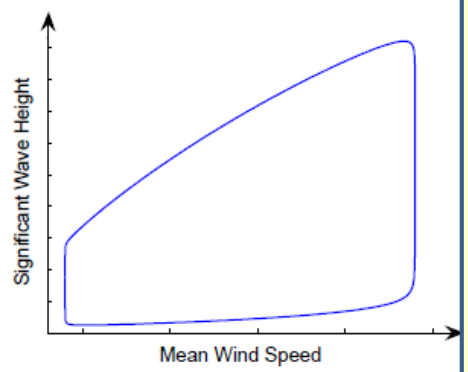
- Try candidate (V, H_s) pairs
  Derive seastate-specific load fractile, p_3 that must be estimated from simulations (by *extrapolation*)

$$p_3 = 1 - \Phi\left(\left(\beta^2 - \left[\Phi^{-1}(F_V(v))\right]^2 - \left[\Phi^{-1}\left(F_{H_s|V}(h|v)\right)\right]^2\right)^{1/2}\right)$$

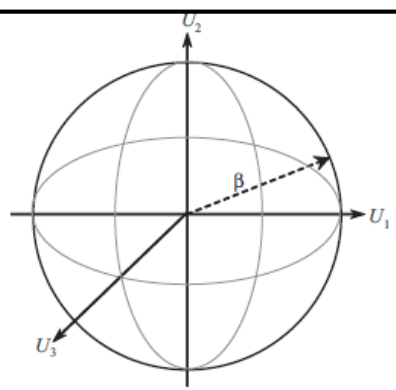
- Solution: The p_3-fractile load that is the largest (of all choices)
- Note: $p_3 = 0.5$ ($u_3 = 0$) is the ***Environmental Contour*** approach used in the oil & gas industry. Also, to define $H_{s,SSS}(V)$, $\sigma_{ETM}(V)$, etc.

"Extreme" Loads

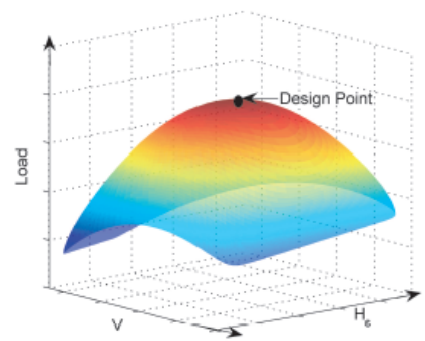




←Mapping from ***U*** space to ***X*** (physical) space of (V, H_s)
Return period → β
$U_1^2+U_2^2 = \beta^2$
$\Phi(u_1)=F_V(v)$;
$\Phi(u_2)=F_{Hs|V}(h|v)$
ENVIRONMENTAL CONTOUR METHOD
Identifies CRITICAL sea states, defines **SSS**, etc.



STANDARD NORMAL



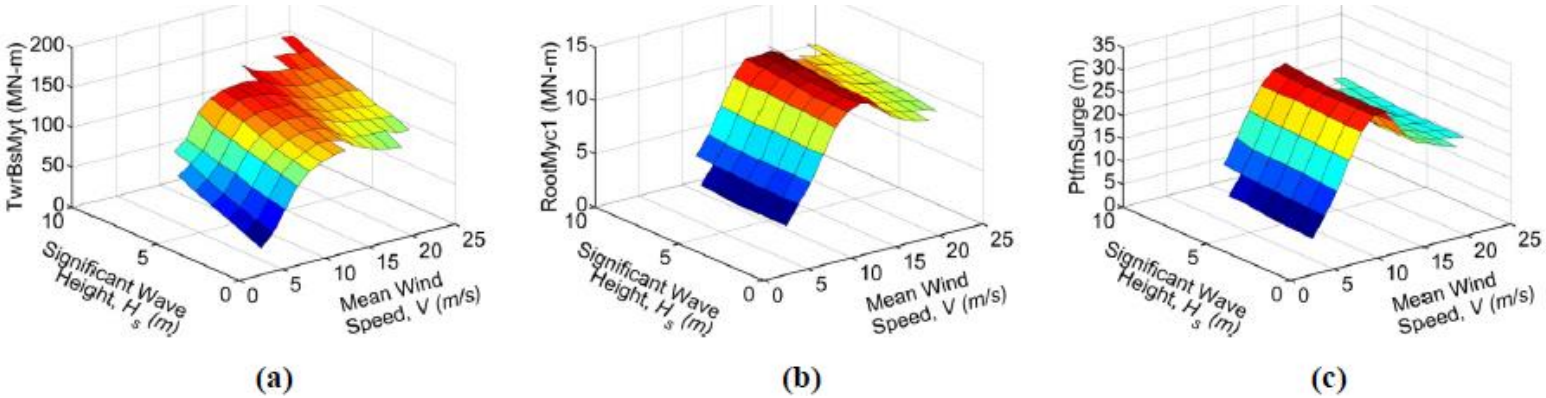
PHYSICAL

←Mapping from ***U*** to ***X*** (as before)
... now, include load, L;
→ $\Phi(u_3)=F_{L|Hs,V}(L|h,v)$
Return period → β
$U_1^2+U_2^2+U_3^2= \beta^2$
Need $F_{L|Hs,V}(L|h,v)$ from OWT load simulations.
Used for DLC 1.1, etc. and load extrapolation.

"Extreme" Loads

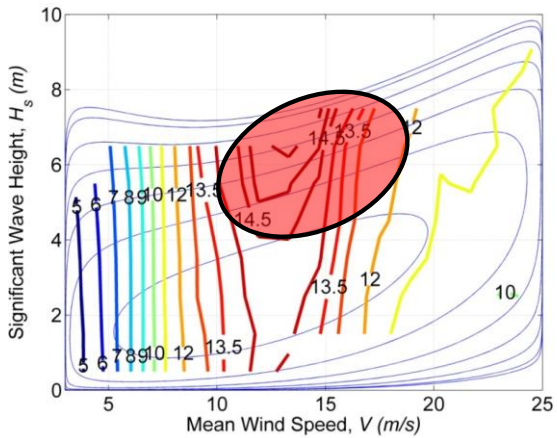
Example: Spar Floating Offshore Wind Turbine

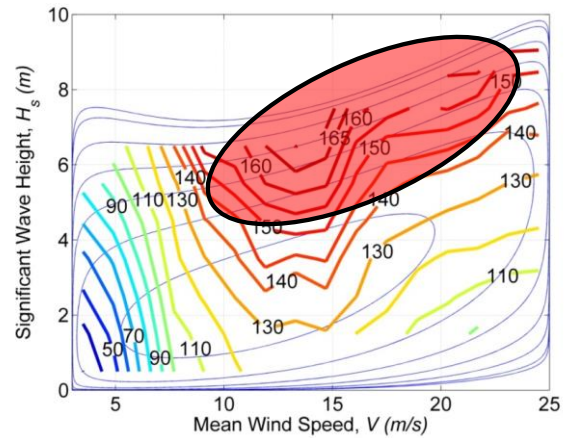
- Shown are median extreme response surfaces (from 25 simulations) for:
  - (a) tower loads
  - (b) blade loads
  - (c) platform surge



- Greater importance of waves for tower loads
- Effect of pitch control is evident in peaks of loads

"Extreme" Loads

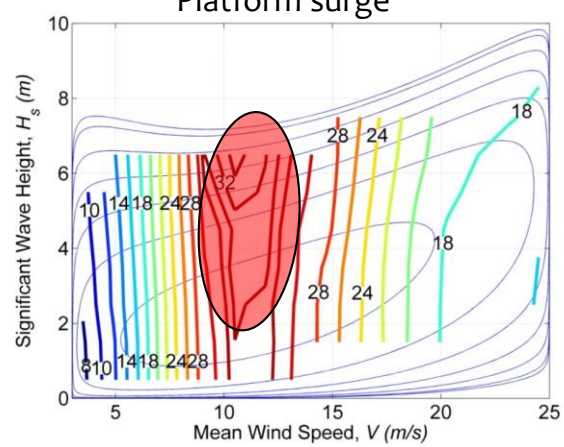




Shaded regions identify (V, H_s) values where the median loads are both large and where they show significant variability.

These are of importance in computing LONG-TERM loads.

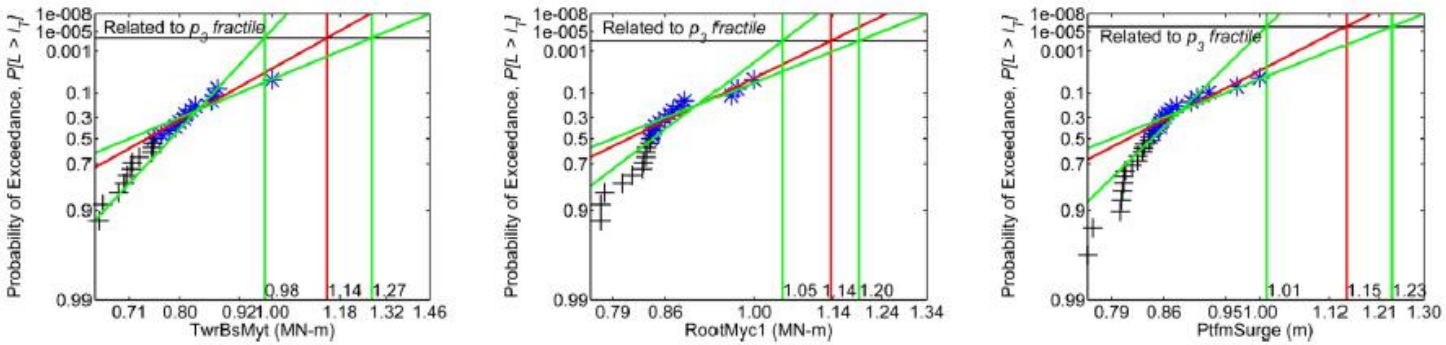
Platform surge



"Extreme" Loads

❖ Weibull-fitted extrapolated load distributions in critical sea states for:

(a) tower loads
(b) blade loads
(c) platform surge



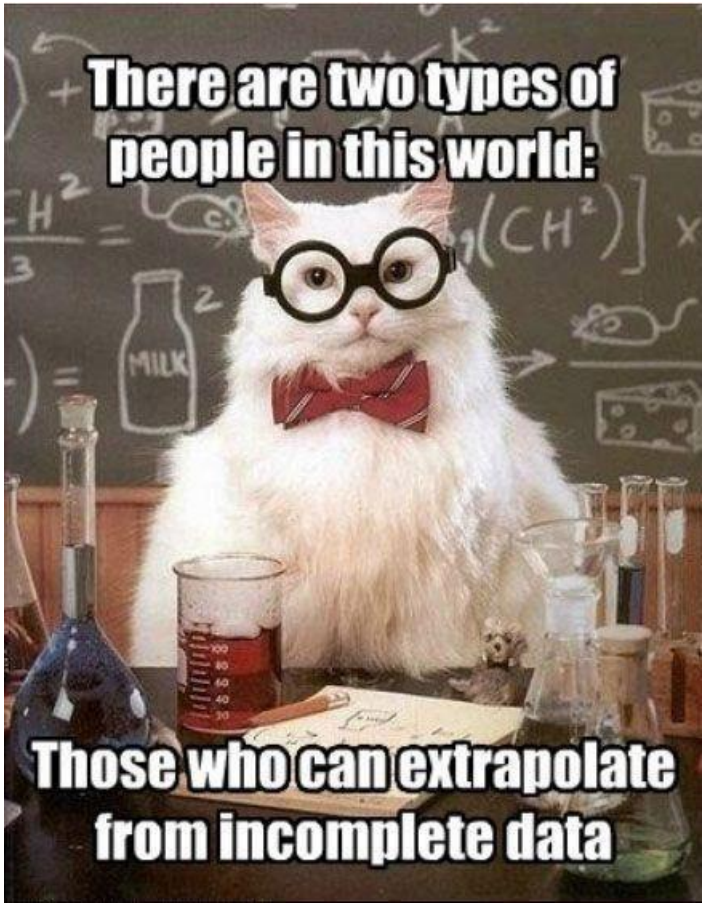
(a) (b) (c)

❖Platform motions are more sensitive to waves; in general, blade and tower load extremes were greatest at or slightly above the turbine's rated wind speed

❖Identified controlling environmental conditions that influence long-term (50-year) response

Sultania & Manuel, OMAE 2011 (doi: 10.1115/OMAE2011-50072)

“Extreme” Loads



Standards: Load Uncertainty

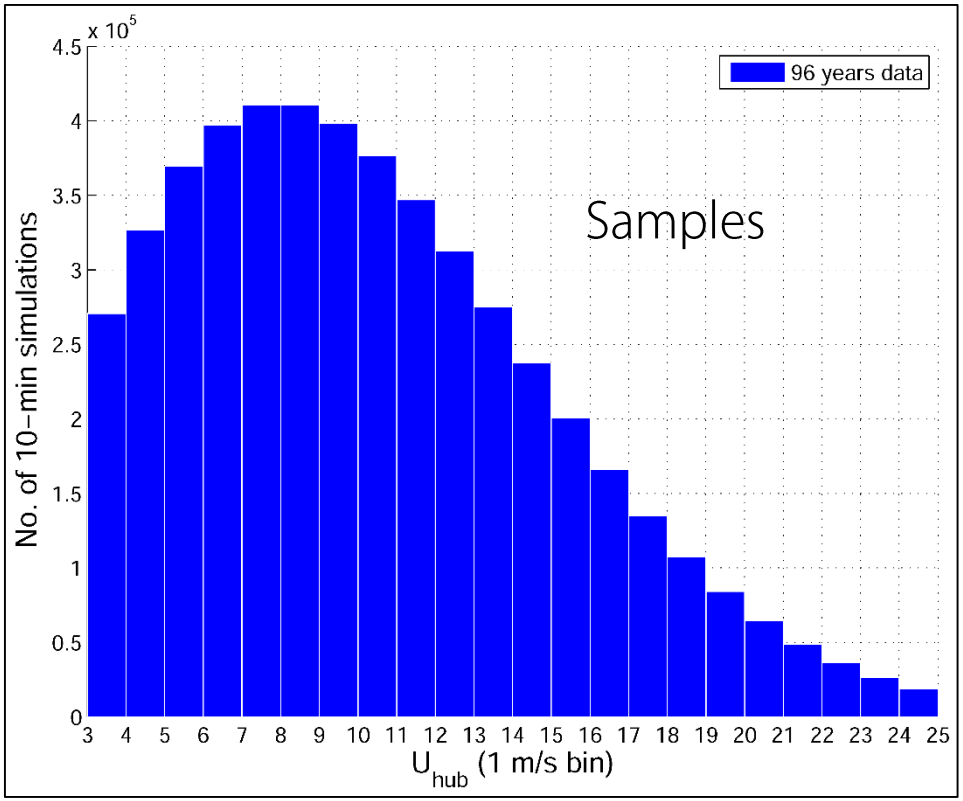
Motivation: Unpopular and tedious computation of 50-year load in DLC 1.1 of IEC 61400-1 is needed in design.
Design Load (Factored) = $1.25 \times L_{50}$

Proposal: Calibrate an alternative to be specified in Clause 7.6.2 that offers an equivalent design load but at lower computational cost

Method: UQ (Sandia's DAKOTA) with HPC resources
Compute "true" 50-year load using an extensive loads database
Calibrate alternative proposal using simpler 10-min max (L_{max}) from a limited no. of simulations over all wind speed bins

Design Load (factored) = $1.25 \times \gamma \times L_{max}$
What is load factor, γ, if properly calibrated?
How many simulations needed per bin?

Standards: Load Uncertainty



What we did ...

96 yrs simulation of 5-MW turbine

Sandia's Red Sky system, a 450 teraflop Linux computing cluster

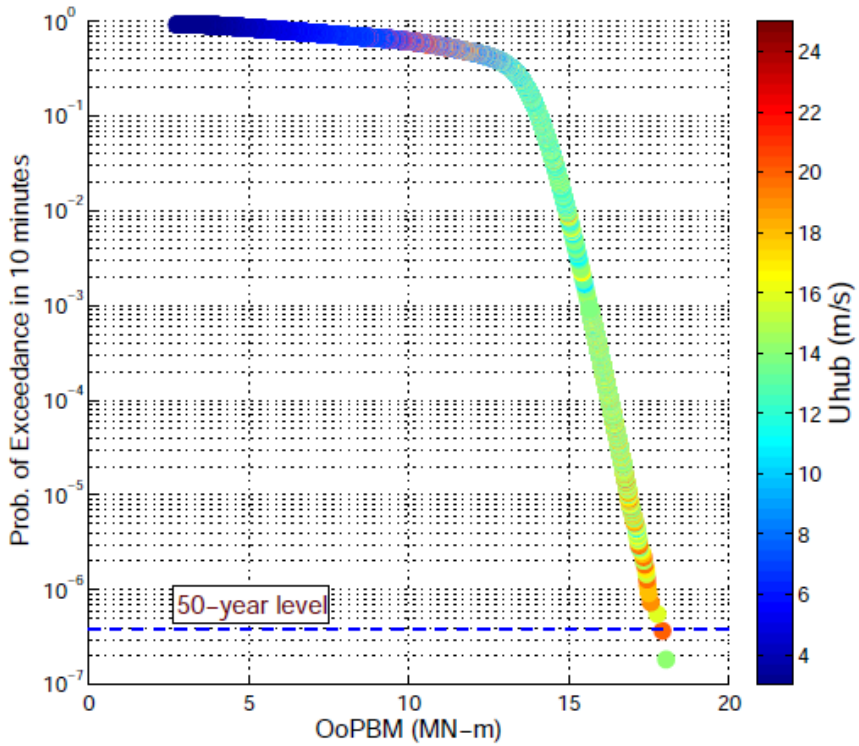
1024 cores of the available 42,440 cores (5305 nodes x 8 CPU cores)

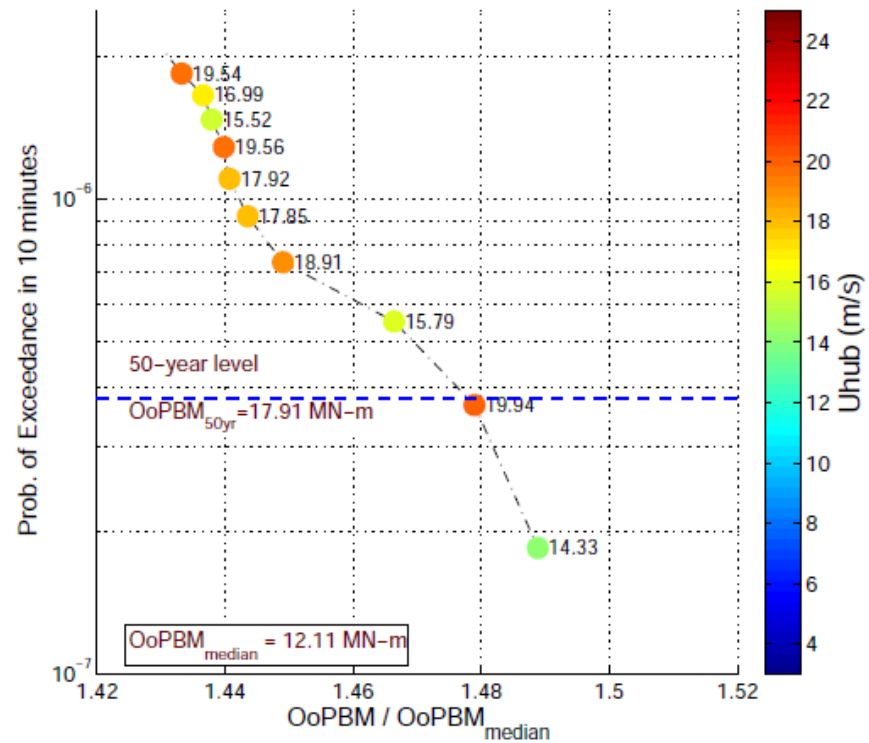
Approx. 104 yrs of service of IEC Class I-B turbine

Approx. 108 wall-clock hours to run

5,020,189 10-min simulations
[e.g., 18,819 in 24-25 m/s bin]

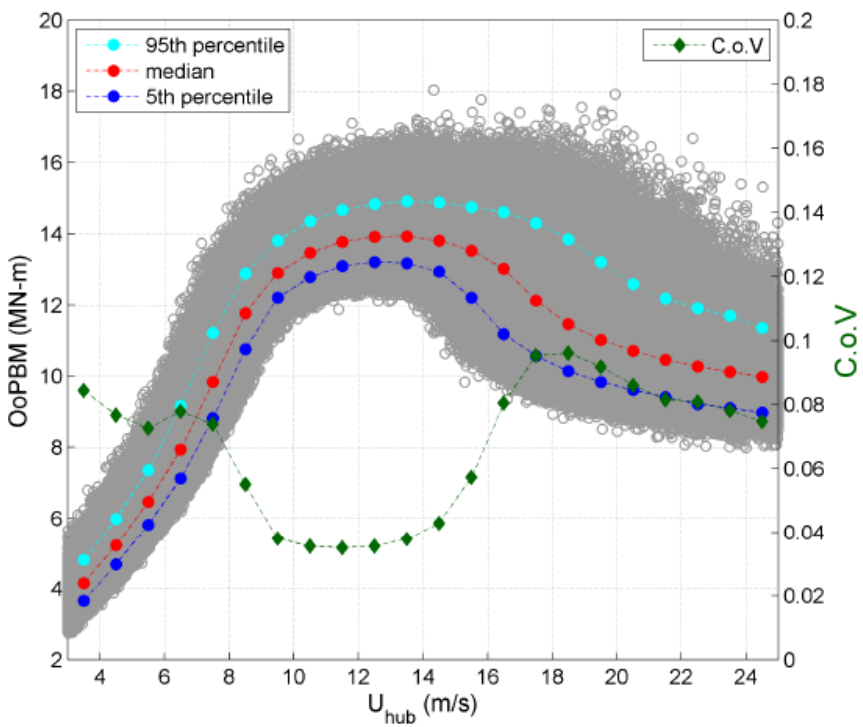
Standards: Load Uncertainty

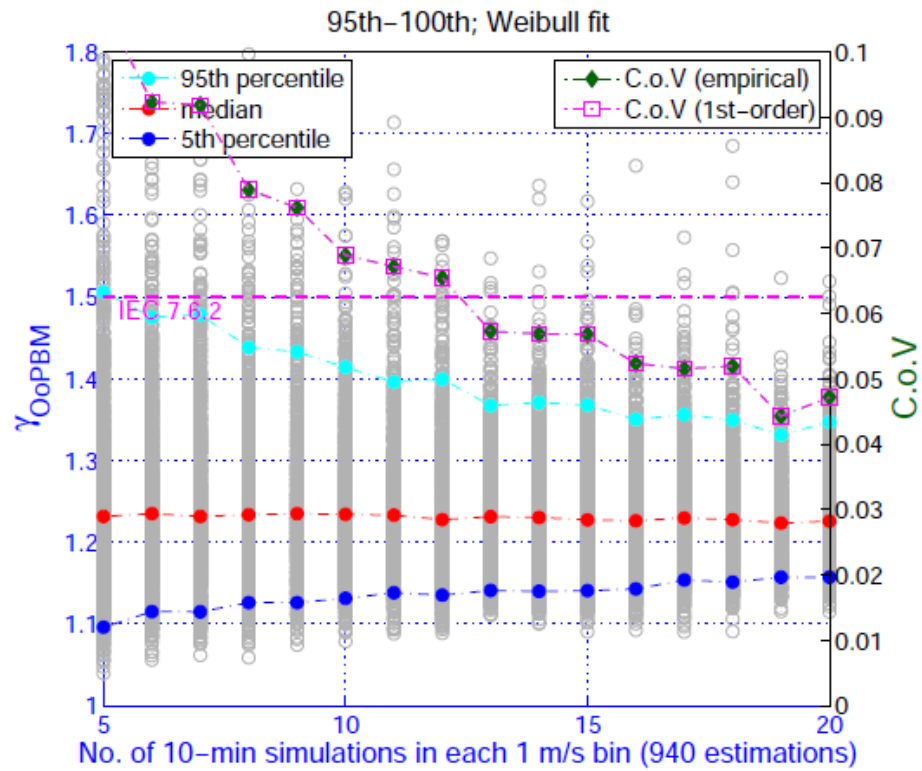




For DLC 1.1 the characteristic value of load shall be determined by a statistical load extrapolation and correspond to an exceedance probability, for the largest value in any 10-min period, of less than or equal to 3.8×10^{-7}, (i.e. a 50-year recurrence period) for normal design situations.

Standards: Load Uncertainty





Standards: Load Uncertainty

For DLC 1.1 the characteristic value of load shall be determined by a statistical load extrapolation and correspond to an exceedance probability, for the largest value in any 10-min period, of less than or equal to **3.8×10^{-7}**, (i.e. a 50-year recurrence period) for normal design situations.

IEC 61400-1 Ed. 4 (REVISED PROPOSAL 7.6.2)
For DLC 1.1 a characteristic value of load shall be determined by a statistical analysis of the extreme loading that occurs for normal design situations and shall correspond to one of the following alternatives:

a) For each wind speed, the characteristic load is obtained as the average of the largest (or smallest) loads from several stochastic simulations at that wind speed, multiplied by a factor of 1.35. This method can only be applied for the calculation of the blade root in-plane moment and out-of-plane moment and tip deflection
b) ...
c) ...

UQ: Response Surrogates

Motivation: Often the variables, processes, fields that are to be modeled involve too many random or uncertain quantities/parameters. We then have a high-dimensional "uncertainty" space. Crude Monte Carlo simulation is prohibitively expensive as each function call may require a high-fidelity full-physics simulation.

Goal: To quantify uncertainty in some response, u.

Physical parameter space, Y, with dependent structure and distributions are mapped to Q. Next, u is expressed using orthogonal polynomials, $\mathbf{\Psi}_i(Q)$.

$$u(x,t,\boldsymbol{Q}) = \sum_{0}^{p} \alpha_i(x,t)\Psi_i(\boldsymbol{Q})$$

Estimate coefficients, α_i, using stochastic collocation, spectral projection, etc. Probe the "truth system" to build model.

UQ: Response Surrogates

Example: Extreme blade-root flapwise bending moment in 10 minutes, U.

Model: Mean wind speed, $X_1 \sim$ Weibull (A, k)
Standard deviation, $X_2|X_1 \sim$ Weibull $(b_0(X_1), b_1(X_1))$
$Y(t) \sim$ Flapwise bending moment (broad-banded, non-Gaussian)
$Y(t) \sim$ Process $(\mu, \sigma, \alpha_3, \alpha_4, \alpha, N_{max})$ – dependent on X_1, X_2, $Z \sim N(0,1)$

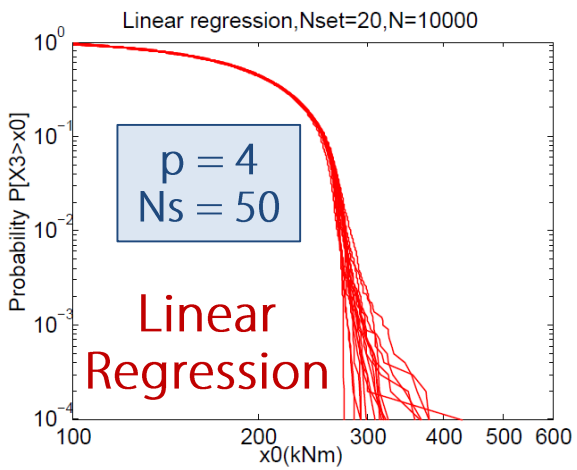
Response: $U \leftarrow X_1, X_2, Z$ (physical) [truth system]
$U' \leftarrow q_1, q_2, q_3$ (standard normal)
$U' \leftarrow$ sum using α_i and $\Psi(q_i)$ [Hermite polynomials]
Estimate U′ and then 10-min extreme
Compare with Monte Carlo Simulation
Note: Variable space can grow to include uncertainty in
$A, k, b_0, b_1, \mu, \sigma, \alpha_3, \alpha_4, \alpha, N_{max}$ (expanded variable space)

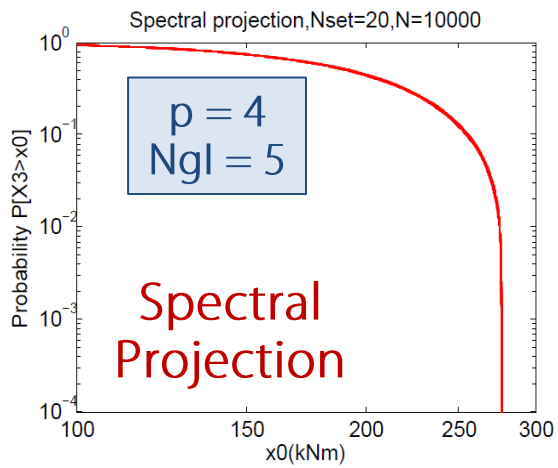
Ref: Larsen, G. C. et al, Risø Report No. 1111, 1999.

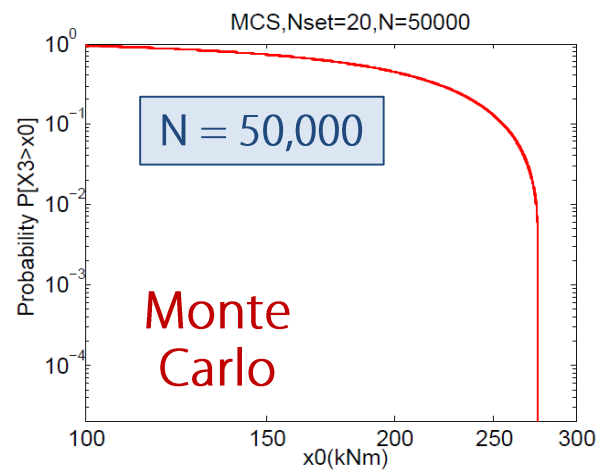
UQ: Response Surrogates

Derived Probability Distribution for:
extreme blade-root flapwise bending moment in 10 minutes

Order of polynomial included = p
No. of truth system evaluations using physics model = Ns (for regression/collocation)
No. of quadrature points per variable = Ngl (for spectral projection)







Ref: Larsen, G. C. et al, Risø Report No. 1111, 1999.

Closing Remarks

- Uncertainties (aleatory and epistemic) arise from
  - the environment (inflow, metocean parameters)
  - imperfect models
  - how we deal with response/performance
  - Interactions

- As the industry has matured, economics and advances in models for flow fields, turbine/plant dynamics/physics have led to higher fidelity truth systems (useful to guide development of lower fidelity systems that can help quantify "key" uncertainties)

- UQ & HPC efforts can aid in validation, in standards, and perhaps even in a shift to plant-level design philosophy

Thank you!

This presentation included work done or included slides prepared by my students:

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