

Probabilistic Wind Turbine System Models in Three Courses: Composite Materials, Aerodynamics, Grid Integration

Dr. Curran Crawford

Department of Mechanical Engineering
University of Victoria

4th Workshop on Systems Engineering for Wind Energy
DTU Vindenergi, September 13, 2017



University
of Victoria

Institute for Integrated
Energy Systems



SSDL

Sustainable Systems
Design Laboratory

Outline

Why Probabilistic Models?

Composite Structures

Turbulent Aero(structural) dynamics

(Smart) Grid Integration

Table of Contents

Why Probabilistic Models?

Composite Structures

Turbulent Aero(structural) dynamics

(Smart) Grid Integration

Wind energy systems inherently involve variability

- ▶ Wind input
 - ▶ High f turbulence
 - ▶ Fat tail distributions (extremes)
 - ▶ Seasonal/annual mean wind speed variation
 - ▶ Decadal-scale variations
- ▶ Wave loading offshore
- ▶ Blade erosion & soiling
- ▶ Large-scale (manual) manufacturing
 - ▶ Limit & fatigue strengths
 - ▶ Stiffness variations
- ▶ Mechanical & electrical component reliability
- ▶ Aero-structural response to these inputs
 - ▶ Controller actions
 - ▶ Fatigue & extreme loads
 - ▶ Power output

System analysis models must handle this variability to be trusted and explore full design space

But we already do this, don't we?

Monte Carlo analyses

IEC load sets + statistical extrapolation

Combined wind/wave conditions

Decomposed MDO frameworks

Quite expensive even for low fidelity BEM-type models

My group's research goals:

Medium fidelity models viable for system optimization

Intrinsically probabilistic models to quantify/mitigate risk

Design studies on advanced concepts, airborne, offshore

Examine system **economics & grid integration**

Table of Contents

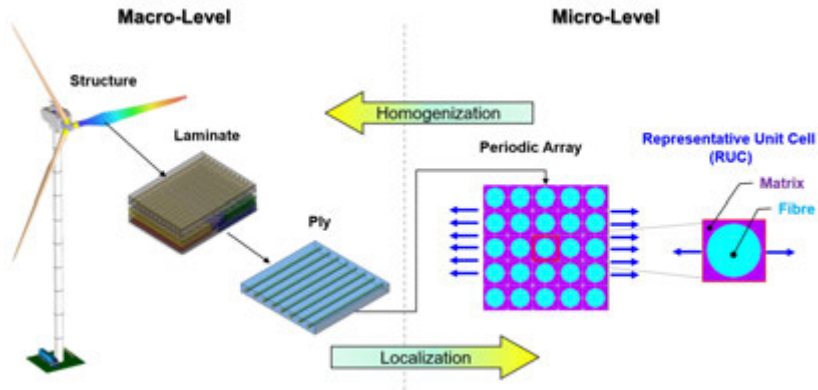
Why Probabilistic Models?

Composite Structures

Turbulent Aero(structural) dynamics

(Smart) Grid Integration

Micromechanics models use matrix & fibre properties avoiding coupon tests for alternative layups



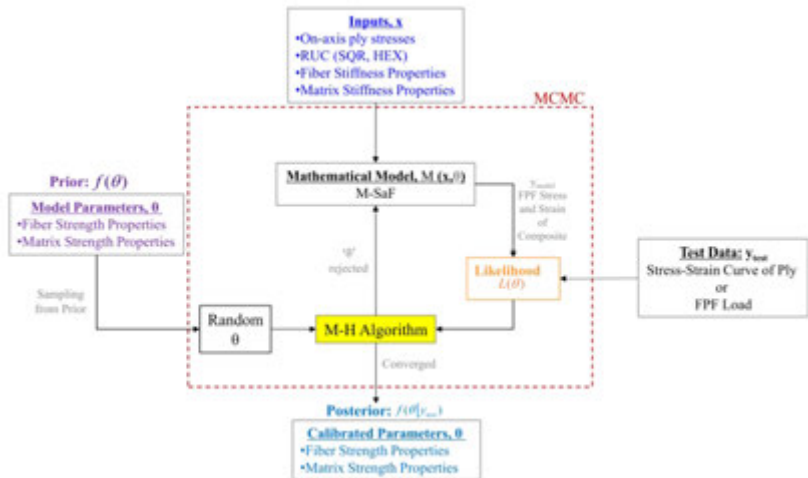
Relate micro $\underline{\sigma}^j$ and macro $\underline{\sigma}$ stresses: $\underline{\sigma}^j = [SAF]\underline{\sigma}$

Elements of SAF computed via FEM simulations

Failure criteria applied at points j based on material strengths

Markov Chain Monte Carlo (MCMC) methods used to evaluate Bayes's theorem estimates

$$f(\Theta|y_{test}) = \frac{f(y_{test}|\Theta)f(\Theta)}{f(y_{test})} = \frac{L(\Theta)f(\Theta)}{f(y_{test})}$$



Statistical strengths calibrated using a limited set of experimental results

Uniform prior (unbiased)

Likelihood function

Assume normal distribution of properties

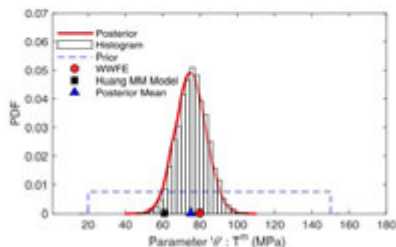
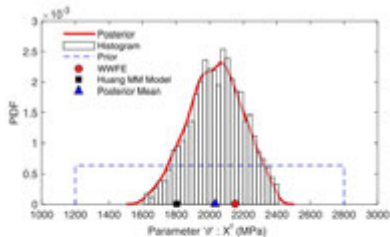
Histogram algorithm output

Kernel density estimator on MCMC results

Fibre and matrix strengths

Compressive, tensile, shear

Ultimate and fatigue



Forward statistical analysis of candidate layups is then possible (ultimate & fatigue)

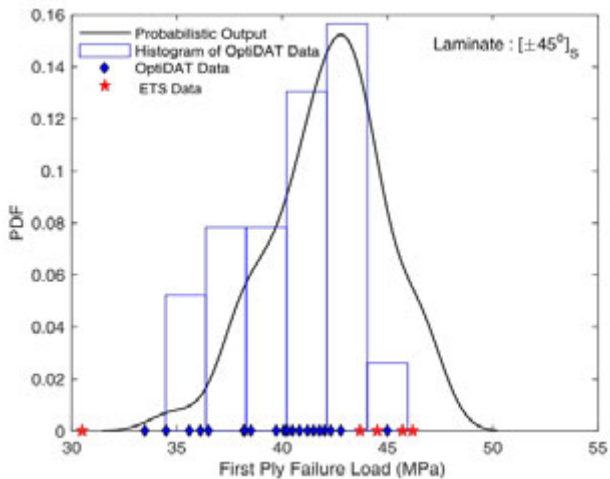


Table of Contents

Why Probabilistic Models?

Composite Structures

Turbulent Aero(structural) dynamics

(Smart) Grid Integration

To explore new (multi-MW scale, floating) concepts, need to get beyond BEM

Physics not captured by BEM

- Non-linear motion & deflections
- Swept/winglet blades

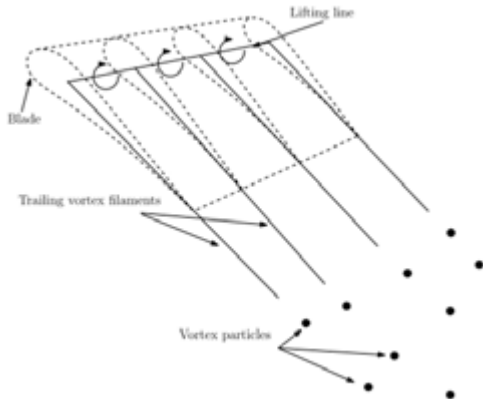
Unsteady aerodynamics

CFD still too costly for unsteady design

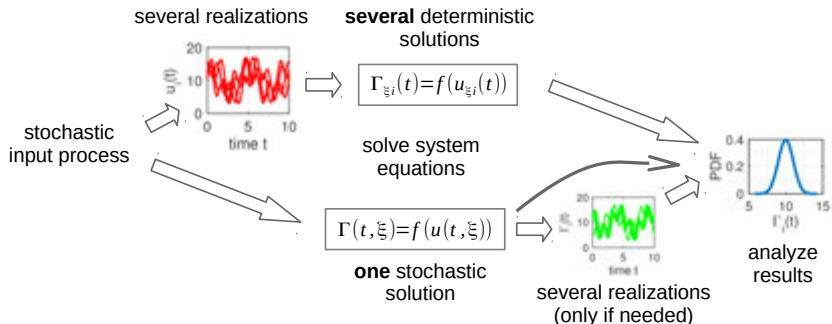
Vortex-based methods appropriate

- But costly for unsteady design

Also want **gradients** for unsteady performance



Fundamentally, we want to replace many time-domain simulations with a single solution in the stochastic space



We have adopted intrusive chaos (polynomial) methods to analyze in the stochastic domain

Expand wind inflow model with random phase angles $\xi \in [-\pi, \pi]$ as:

$$u_{\infty}(t_n, \xi) = \sum_{r=0}^{R-1} \hat{u}_r(t_n) \Psi_r(\xi)$$

** Lots of groundwork on describing correlated wind fields with minimum number of ξ phase angles

Expand circulate strength Γ (lift) as:

$$\Gamma(t_n, \xi) = \sum_{r=0}^{R-1} \hat{g}_r(t_n) \Psi_r(\xi)$$

Functionals $\Psi_r(\xi)$ define polynomials (exponentials) of random variable ξ

Choose form based on PDF of ξ

Legendre polynomials for uniform distributions

Solution procedure is equivalent to one time-domain solve but obtain results for all possible ξ values

Use inner product $\langle \square, \Psi_r(\xi) \rangle$ 'stochastic Galerkin' projection

Orthogonality property of $\Psi_r(\xi)$ when chosen correctly

Equations for coefficients in time fall out

$$\hat{u}_r(t_n) \quad \hat{g}_r(t_n)$$

Note that these solutions are functions of time

Not a Fourier transform!

Can handle non-linear, time dependent effects

Output quantity calculations

Time-domain for specific ξ realization

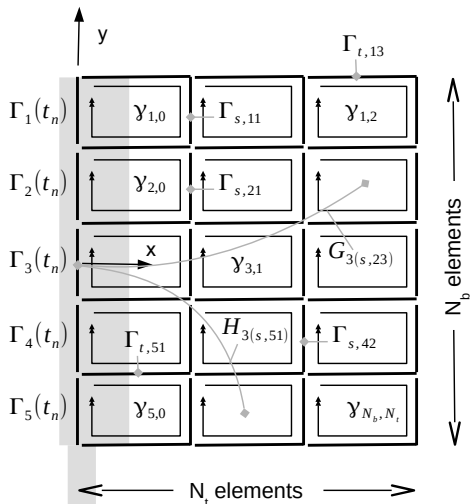
Validation with time dependent code

Directly compute statistical moments from $\hat{g}_r(t_n)$

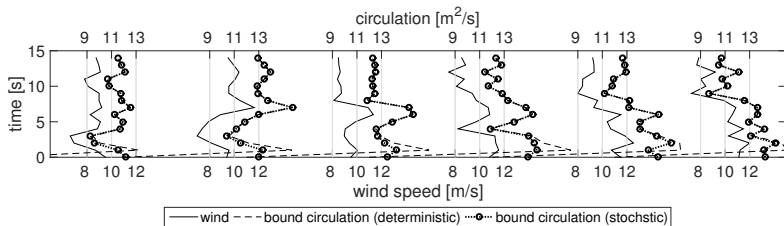
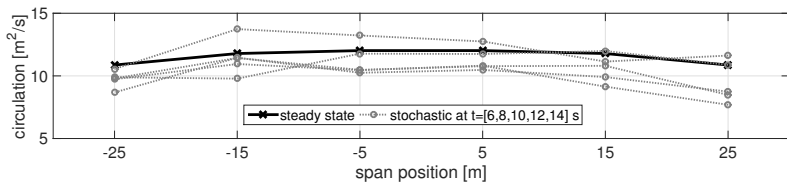
PDF reconstruction methods

All possible wind input fields evaluated simultaneously

We've applied the stochastic Galerkin method to stationary blades/wings (lifting line)...



We've applied the stochastic Galerkin method to stationary blades/wings (lifting line)...



... and simplified BEM compared to 100 deterministic sample wind inputs

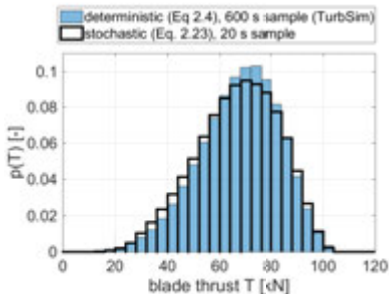
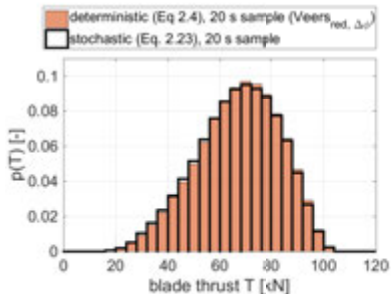
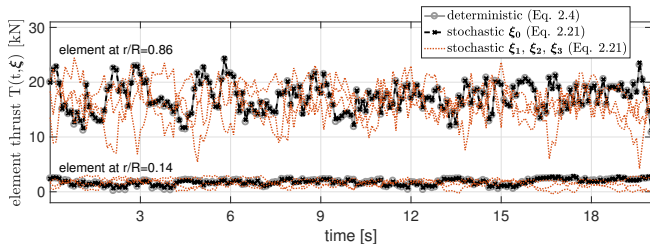


Table of Contents

Why Probabilistic Models?

Composite Structures

Turbulent Aero(structural) dynamics

(Smart) Grid Integration

Wind energy's value depends on the grid-delivered product, hopefully greater than the costs to provide it

Various components in levelized cost of energy

- Base materials – capital costs

- Aerostructural performance – power capture/loads

- Variability in system costs captured with previous approaches

But value is different than costs

- Levelized avoided cost of energy (LACE)

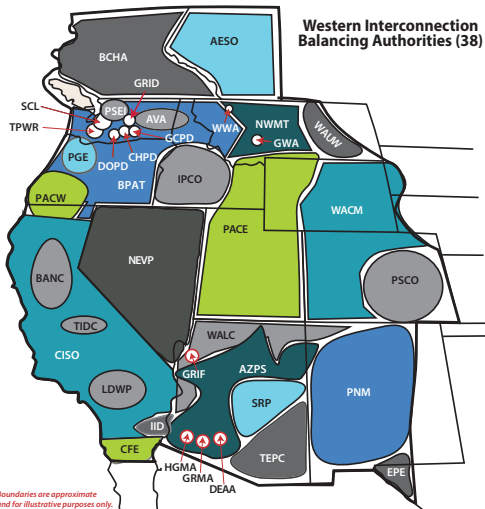
 - LCOE estimates revenue *requirements*

 - LACE estimates revenues *available*

- Firming services costs

How to model variable grid system performance?

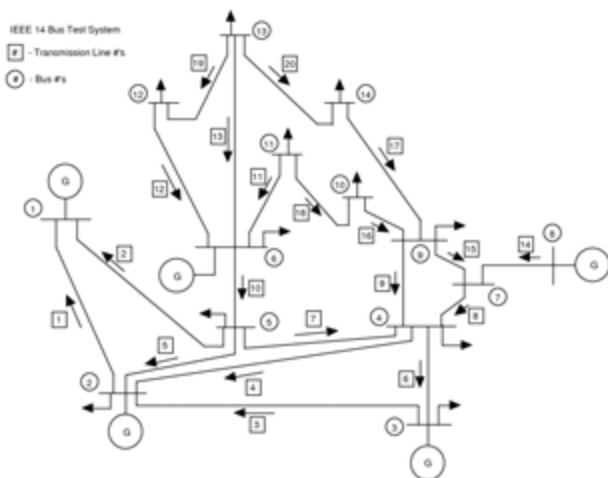
The interconnected grid is large and complicated, requiring efficient solutions methods



The power grid is modeled by a set of (non-)linear power flow equations

Distribution and transmission grid governing equations

$$[P_i, Q_i] = f(V_i, \delta_i) \quad [P_{ik}, Q_{ik}] = f(V_i, V_k, \delta_{ik})$$



Cumulant-based analysis methods to handle stochastic generation and loads on each bus

Input definition

Real P_i and imaginary Q_i power injections represent generation and loads on each bus

Compute moments μ_ν of the distributions

Convert moments to cumulants κ_ν of those distributions

Analysis method

Basic cumulant arithmetic for $Y = AX$: $\kappa_{Y,\nu} = A^\nu \kappa_{X,\nu}$

We extended to cumulant tensors for **correlated** variables and polynomial functionals

Linearize polar form of equations & truncate

Rectangular form of power flow equation expansion

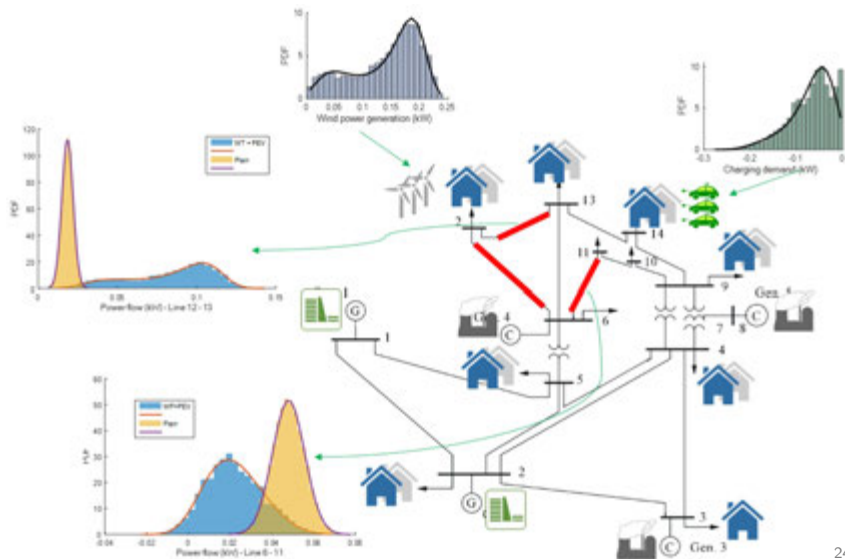
⇒ exact quadratic equation!

Post-process results

$[V_i, \delta_i, P_{ik}, Q_{ik}]$ outputs impacting costs, etc.

Maximum-entropy PDF reconstruction from κ_ν

IEEE 14 bus example with wind power generation and plug-in vehicle loads



Thanks for listening!

Dr. Curran Crawford

E-mail curranc@uvic.ca

Website www.ssdl.uvic.ca

Twitter [@SSDLab](https://twitter.com/SSDLab)

Students

Composites Ghulam Mustafa

Aero Manuel Fluck, Rad Haghi

Grid Trevor Williams, Pouya Amid