Large-Scale Uncertainty and Error Analysis for Time-dependent Fluid/Structure Interactions in Wind Turbine Applications

Background & Motivation

The design and operation of wind turbines is critically affected by uncertainties

- Different scenarios and drivers are considered for wind turbine design:
  - fatigue and extreme load survivability
  - aerodynamic performance and low environmental impact (noise)
- Two types of uncertainties are expected to affect the overall turbine behavior:
  - Natural stochasticity (aleatory uncertainty): wind profile, dust/insect contamination, material properties, etc.
  - Physical model bias (epistemic uncertainty): laminar/turbulent transition, aero-structural coupling, wake turbulence, etc.

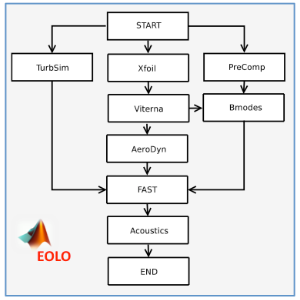
Objectives of the project

- Develop, employ and critically compare novel methodologies for UQ in wind turbine applications
- Use gradient information and goal-oriented adaptivity to reduce the computational effort in evaluating statistics of the quantities of interest
- Distinguish and estimate the importance of numerical errors, aleatory and epistemic uncertainties
- Establish criteria for multi-fidelity simulations
- Disseminate UQ technologies to wind energy community

Horizontal Axis Wind Turbine — *Vertical Axis Wind Turbine*

Multi-physics Wind Turbine Simulations

Wind Turbines are multi-physics devices, need comprehensive prediction tools

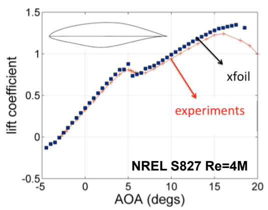


- We developed the EOLO framework
- Based on NREL tools
- Includes aerodynamics, structural dynamics, turbulent wind flows, noise
- The aerodynamic analysis are based on xfoil (low-fidelity flow prediction tool) rather than experimental correlation
- Blade stall and transition behavior are characterized using semi-empirical models (Viterna and e^N, respectively)
- EOLO is driven by matlab and interfaced with Dakota

Prediction of the aerodynamic loads is a critical components

- EOLO predictions are compared to experiments for the NREL S827 airfoil, designed specifically for wind turbines
- In spite of the unorthodox aerodynamic behavior (kink in the lift curve) EOLO computations are in very good agreement with the measurements

Validation of Aerodynamic Loads



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Uncertainty Quantification Methodology

The use of gradient evaluations as a enhancement to classic stochastic collocation techniques is one of the main drivers of the algorithmic development

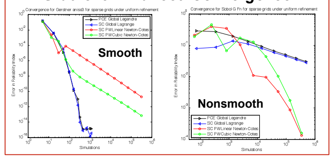
- Polynomial chaos and stochastic collocation methods based on sparse grids are available in DAKOTA
- Extensions to include gradient information have been developed
- For interpolants, generalized quadrature rules are defined…

$$\mu = \sum_{i=1}^{N} f_i w_i^{(1)} w_i^{(1)} w_i^{(1)} + \sum_{i=1}^{N} \frac{df_i}{dx_1} w_i^{(2)} w_i^{(1)} w_i^{(1)} + \sum_{i=1}^{N} \frac{df_i}{dx_2} w_i^{(1)} w_i^{(2)} w_i^{(1)} + \sum_{i=1}^{N} \frac{df_i}{dx_3} w_i^{(1)} w_i^{(1)} w_i^{(2)}$$

…as well as surface response reconstruction

$$f = \sum_{i=1}^{N} f_i H_i^{(1)}(x_1) H_i^{(1)}(x_2) H_i^{(1)}(x_3) + \sum_{i=1}^{N} \frac{df_i}{dx_1} H_i^{(2)}(x_1) H_i^{(1)}(x_2) H_i^{(1)}(x_3) + \sum_{i=1}^{N} \frac{df_i}{dx_2} H_i^{(1)}(x_1) H_i^{(2)}(x_2) H_i^{(1)}(x_3) + \sum_{i=1}^{N} \frac{df_i}{dx_3} H_i^{(1)}(x_1) H_i^{(1)}(x_2) H_i^{(2)}(x_3)$$

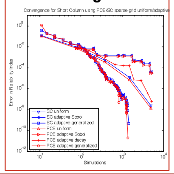
Gradient Enhanced Convergence



- An additional thrust of the algorithmic work is the definition of p-/h-refinement strategies:

a) Uniform: *isotropic* tensor/ sparse grids
b) Adaptive: *anisotropic* tensor/sparse grids
c) Goal-oriented adaptive: *generalized* sparse grids

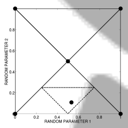
p-refinement Strategies

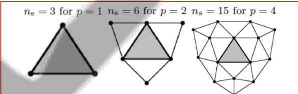


As a more flexible alternative to hypercube-based discretization of the parameter space we are considering the Simplex Stochastic Collocation method

- Simplex elements discretization of probability space
- Delaunay triangulation and solution adaptive refinement
- Randomized sampling for efficiency in higher dimensional probability spaces
- High degree interpolation stencils
- Superlinear convergence for smooth responses
- Robust approximation of discontinuities using Local Extremum Diminishing (LED) limiter

Random refinement in sub-simplex

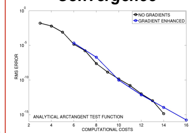




Stencils for high-order reconstructions

- Inclusion of gradient information has been completed
- Test case in 1D shows that gradient information at a node is equivalent to one additional function evaluation
- Extension to multi-dimensions ongoing with potential of extensive efficiency gain

Gradient Enhanced Convergence

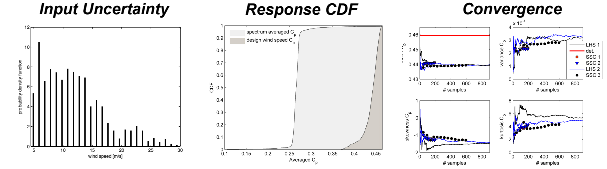


Uncertainty Quantification for Wind Turbine

Evaluation of energy extraction and noise under uncertainty in wind condition (speed) and surface perturbations (dust, bugs)

- **Input Uncertainty**: Speed velocity as a discrete histogram distribution and geometry perturbations as "assumed" continuous distributions (3 input variables).
- **Output Metric**: Energy extraction (aerodynamic loading) and noise
- **UQ Methods**: LHS and SSC (adaptive with 24/48 realizations added at each iteration)
- **Response function evaluations**: 1k LHS samples for moments evaluation; up to 600 for SSC/PCE (in Fig. below SSC1 and SSC2 use 200 realizations and SSC3 uses 600)

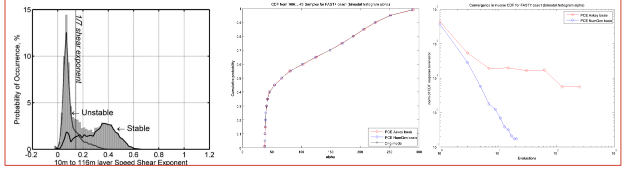
Input Uncertainty — *Response CDF* — *Convergence*



Evaluation of fatigue under uncertainty in wind condition (shear)

- **Input Uncertainty**: Speed shear exponent as continuous histogram distribution.
- **Output Metric**: Blade root out-of-plane bending moment amplitude during steady limit cycle.
- **UQ Methods**: LHS and PCE with Askey/Gauss-Patterson or numerically generated/Gauss using p-refinement (isotropic/anisotropic/generalized essentially equivalent for 1-D).
- **Response function evaluations**: 100k LHS samples for PDF/CDF eval (truth or approx); up to 255 for Askey PCE (level w=7); up to 21 for NumGen PCE (level w=10).

Input Uncertainty — *Response CDF* — *Convergence*

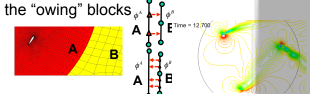


Towards Multi-fidelity Modeling

As a step towards high fidelity aero-mechanics simulations of (vertical-axis) wind turbines, we investigated the use of moving meshes and Time-Spectral methods

The sliding mesh technology being evaluated is based on a novel DG formulation built upon DOE's ASC SIERRA T/H CVFEM code base

Numerical fluxes are evaluated on each of the "owing" blocks



$$\int_{\Omega_B} w\left(\frac{\partial \rho\phi}{\partial t} - S_\phi\right) d\Omega - \int_{\Omega_B} F_j \frac{\partial w}{\partial x_j} d\Omega + \int_{\Gamma \setminus \Gamma_{AB}} w F_j n_j d\Gamma + \int_{\Gamma_{AB}} w \hat{F}^B d\Gamma = 0$$

$$\int_{\Omega_A} w\left(\frac{\partial \rho\phi}{\partial t} - S_\phi\right) d\Omega - \int_{\Omega_A} F_j \frac{\partial w}{\partial x_j} d\Omega + \int_{\Gamma \setminus \Gamma_{AB}} w F_j n_j d\Gamma + \int_{\Gamma_{AB}} w \hat{F}^A d\Gamma = 0$$

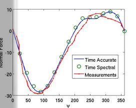
$$\hat{F}^A = \frac{1}{2}\left[\left(F_j^A n_j^A - F_j^B n_j^B\right) + \lambda(\phi^A - \phi^B)\right]$$

The second order accurate formulation allows for detailed meshing at the wind turbine blades

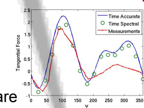
The time-spectral method takes advantage of temporal periodicity and replaces the time-marching algorithm with a Fourier-based representation (but in the time-domain) that can be solved as a pseudo steady-state problem.

$$\frac{\partial u}{\partial t} + R(u) = 0 \rightarrow \frac{\partial u^n}{\partial t'} + D_t u^n + R(u^n) = 0$$

$$D_t u^n = \sum_{m=-\frac{N}{2}+1}^{k=\frac{N}{2}-1} d_m u^{m+n}$$



This allows for large savings in computational cost and feasible adjoint solutions. Figures compare 128 steps/rev time marching vs 16 time-spectral instances.



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