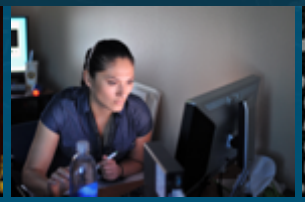
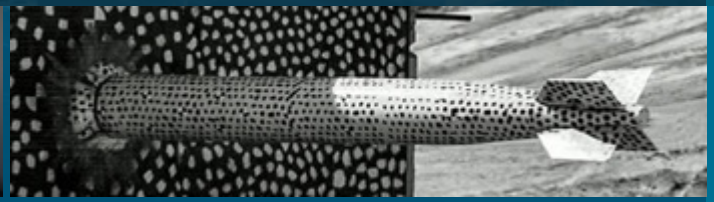
Sandia National Laboratories

SAND2020-13779C

Multifidelity Uncertainty Quantification of Wind Turbine Interaction Using Enhanced Nalu-Wind Actuator Simulations





PRESENTED BY

A.S. Hsieh, D.C. Maniaci, and G. Geraci

U.S. DEPARTMENT OF ENERGY | NNSA

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

Presentation Overview

Motivation and Multifidelity UQ

Sub-Models Overview

Present Results and Comparison to Previous Work

Motivation and Multifidelity UQ

Motivation

- Accurate uncertainty quantification (UQ) for predictive wind simulations requires large amount of simulations (reduce variance)
- High-fidelity (HF) simulations are needed for accurate wind farm predictions and modeling of complex atmosphere-turbine-wake interactions (reduce bias)
- **Problem**: Running large amounts of HF simulations reduces both variance and bias, but with often excessive computational costs
- **Solution**: Multifidelity UQ leverages cheaper, lower accuracy models with a handful of HF computations to significantly mitigate computational costs

Sampling Strategy Categories

- Monte Carlo (MC) uses a simple, robust sampling-based approach using a single model at the same resolution, but has a slow rate of convergence
- Multilevel Monte Carlo (MLMC) approaches use the convergence of model resolutions (temporal and spatial) to build corrections for coarsest levels and reduce deterministic errors
- Multilevel-Multifidelity (MLMF) approaches combine MLMC with control variates (CV) using lower fidelity models to reduce both stochastic and deterministic errors

Motivation and Multifidelity UQ

Current Research Scope

- Evaluate effectiveness of multifidelity UQ for wind farm applications
- Achieve better understanding of how multifidelity UQ can be best optimized for wind farm applications

Previous Work

Maniaci, D.C. et al., "Multilevel uncertainty quantification of a wind turbine large eddy simulation model." 7th European Conference on Computational Fluid Dynamics. 2018.

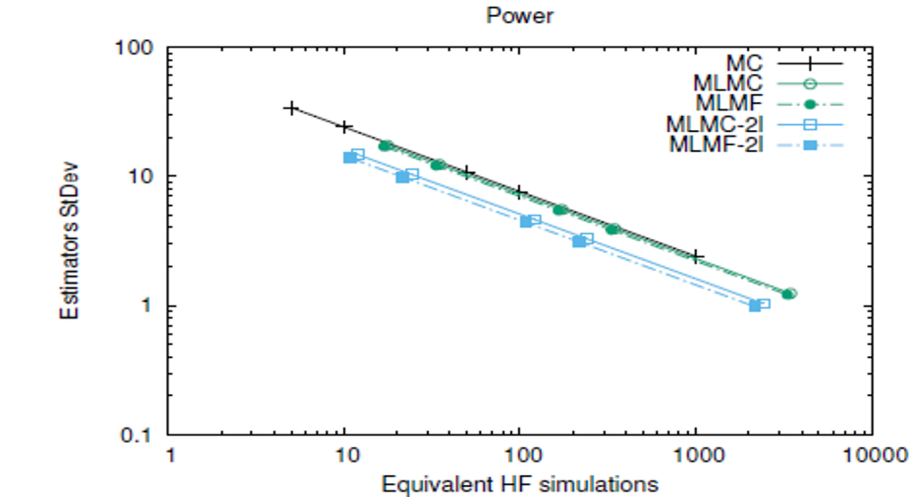
- Initial MLMF study using Nalu-Wind and OpenFAST

Hsieh, A.S. et al., "Multilevel Uncertainty Quantification Using CFD and OpenFAST Simulations of the SWiFT Facility." Presented at the 2020 AIAA SciTech Forum.

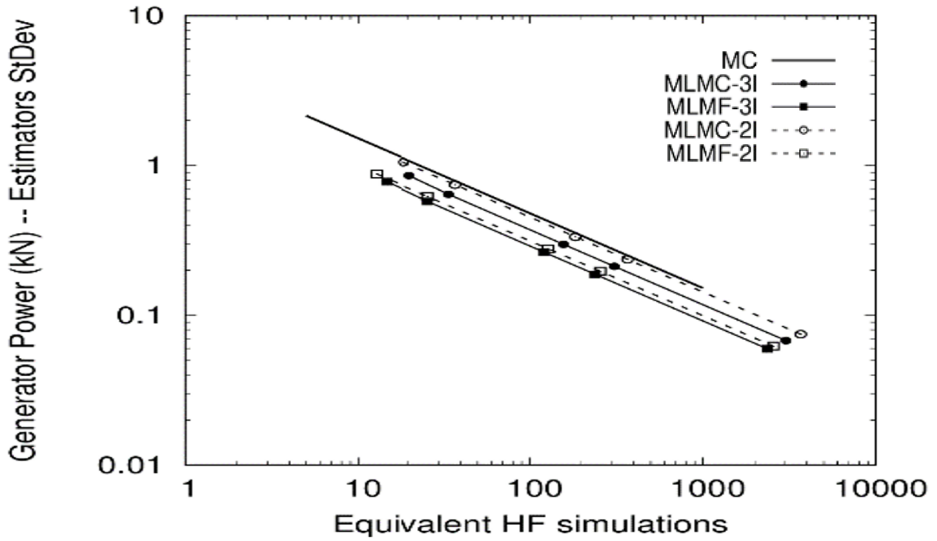
- Second major MLMF study using Nalu-Wind and OpenFAST with benchmark-level simulation methodology and meshes

Present Study

- Present UQ study used the same simulation methodology, meshes, and uncertain inputs as the Hsieh et al. (2020) study
- Major Differences: Nalu-Wind actuator code refactoring in 2020 resulted in significantly faster Nalu-Wind actuator line and disk simulations; change in Nalu-Wind simulation parameter epsilon (actuator spreading force width)



(Maniaci et al., 2018)



(Hsieh et al., 2020)

Presentation Overview

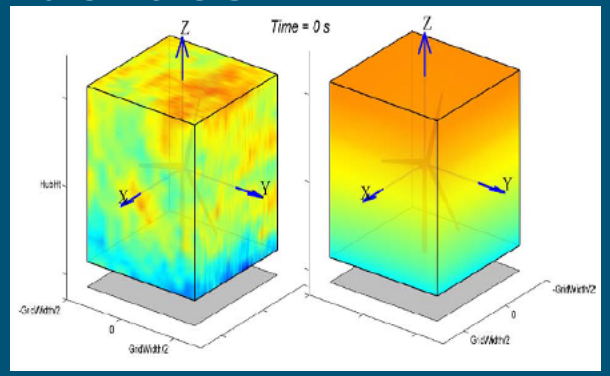
Motivation and Multifidelity UQ

Sub-Models Overview

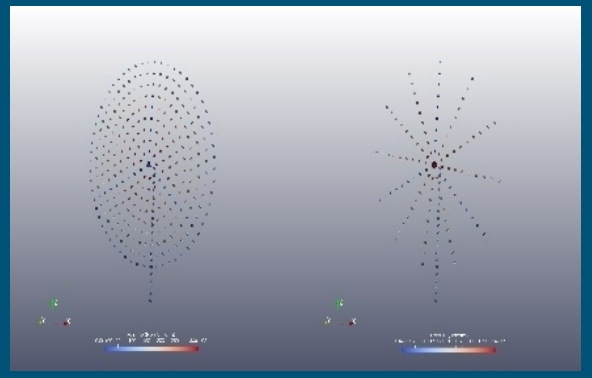
Present Results and Comparison to Previous Work

MLMF Sub-Models Overview

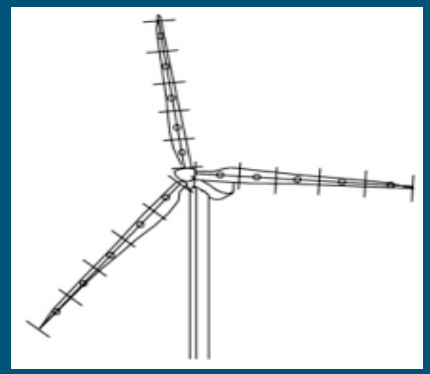
Multilevel-Multifidelity sampling requires selection of varying model fidelities



TurbSim Inflow (TurbSim Documentation)



Actuator Disk Force Distribution (Nalu-Wind Documentation)



Actuator Line Force Distribution (Nalu-Wind Documentation)

Low-fidelity model

- TurbSim + OpenFAST
  - TurbSim: Low-cost spectral turbulence model
  - OpenFAST: Wind turbine dynamics model

Mid-fidelity model

- Nalu-Wind Actuator Disk (Nalu-AD) + OpenFAST
  - Nalu-Wind: Massively parallel large-eddy simulation (LES) code
  - Actuator Disk: Constant body-force applied over entire rotor

High-fidelity model

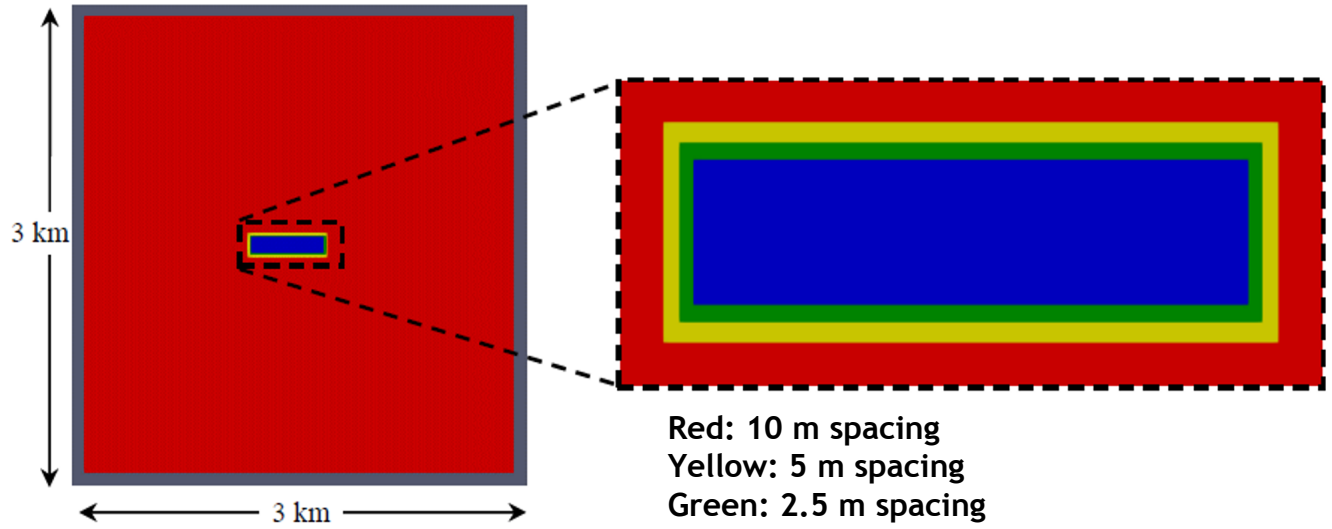
- Nalu-Wind Actuator Line (Nalu-AL) + OpenFAST
  - Nalu-Wind: Massively parallel large-eddy simulation (LES) code
  - Actuator Line: Body-forces applied over blade-like lines

MLMF Sub-Models Overview

Nalu-Wind Simulation Meshes

- Domain size: 3 km x 3 km x 1 km
- Refinement regions around turbine
- Coarse (C) Mesh: 2 ref. levels, 11.7 million elements, Δx_{min} = 2.5 m
- Fine (F) Mesh: 3 ref. levels, 11.7 million elements, Δx_{min} = 1.25 m

Bottom view of mesh with zoomed-in view of refinement regions



Red: 10 m spacing
Yellow: 5 m spacing
Green: 2.5 m spacing
Blue: 1.25 m spacing (F) / 2.5 m spacing (C)

Simulation Model Levels

Case	ID	Simulation Time (hrs)	CPUs	Cost (CPU-hours)	Cost (relative)
OpenFAST + TurbSim	OpenFAST	0.25	1	0.25	1
Nalu-Wind + AD coarse	Nalu-ADC	5.25	768	4,032	16,128
Nalu-Wind + AD fine	Nalu-ADF	6.5	768	4,992	19,968
Nalu-Wind + AL fine	Nalu-ALF	24	768	18,432	73,728

Presentation Overview

Motivation and Multifidelity UQ

Sub-Models Overview

Present Results and Comparison to Previous Work

Present Results and Comparison to Previous Work

Five aleatoric uncertain turbine inputs

- Lower and upper bounds were informed by experimental data from the Sandia-operated SWiFT facility in Lubbock, TX

Quantities of interest (QoIs): 10-min means

- Generated power, rotor thrust, flapwise/edgewise blade-root bending moments, flapwise/edgewise damage equivalent moments (DEM)

Sandia-based Dakota UQ tool used to generate samples

Present study showed the expected significant Nalu-Wind efficiency gains over the previous Hsieh et al. (2020) study

- Computational costs are a significant factor for how the different sampling strategies fare

Sampling Study Aleatoric Uncertain Inputs

Input Variable	Units	Lower Bound	Upper Bound
Yaw Offset	(deg)	-25	25
Generator Torque Constant	(N-m/rpm^2)	0.0003	0.0004
Collective Blade Pitch	(deg)	-1.5	0
Gear Box Efficiency	(%)	90	100
Blade Mass Scale Factor	(-)	0.9	1.1

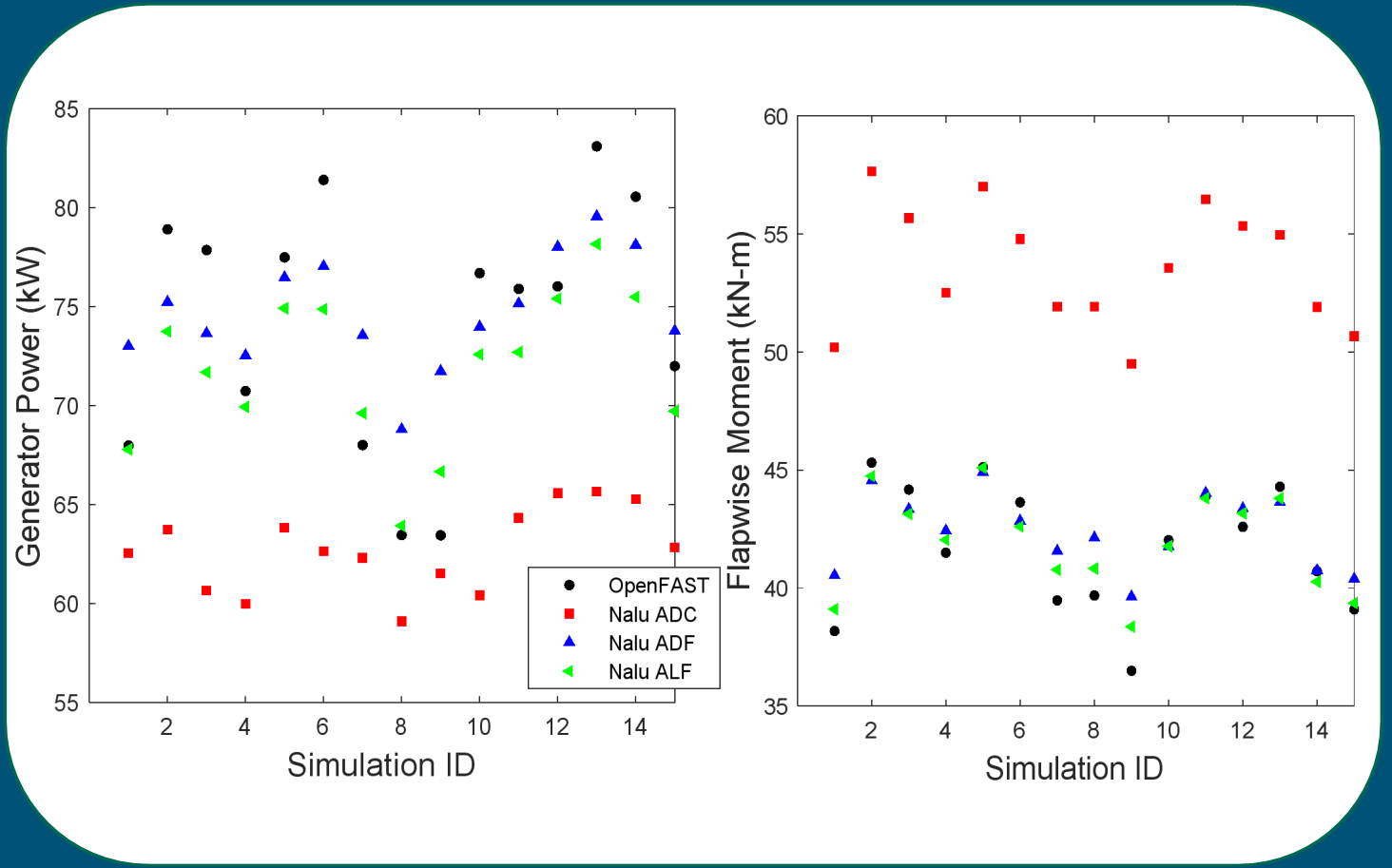
Comparison of Nalu-Wind simulation times between present study (New) and Hsieh et al. (Old)

Case	Old Cost (CPU-hours)	New Cost (CPU-hours)	% Decrease
Nalu-Wind + AD coarse	5,376	4,032	25
Nalu-Wind + AD fine	12,672	4,992	60.6
Nalu-Wind + AL fine	24,384	18,432	24.4

Present Results and Comparison to Previous Work

Comparison of computed QoI values between the present results and Hsieh et al. (2020)

- Significant changes to Nalu-Wind QoI results in present study due to epsilon change
- Nalu-Wind ALF and ADF results are now much closer to OpenFAST values than before
- Nalu ADC results now differ significantly from Nalu ADF results unlike in Hsieh et al. (2020)
- For the present results, the MLMC condition of model level convergence was only satisfied for generator power and rotor thrust. In Hsieh et al. (2020), all QoIs showed monotonic convergence of the multilevel estimators



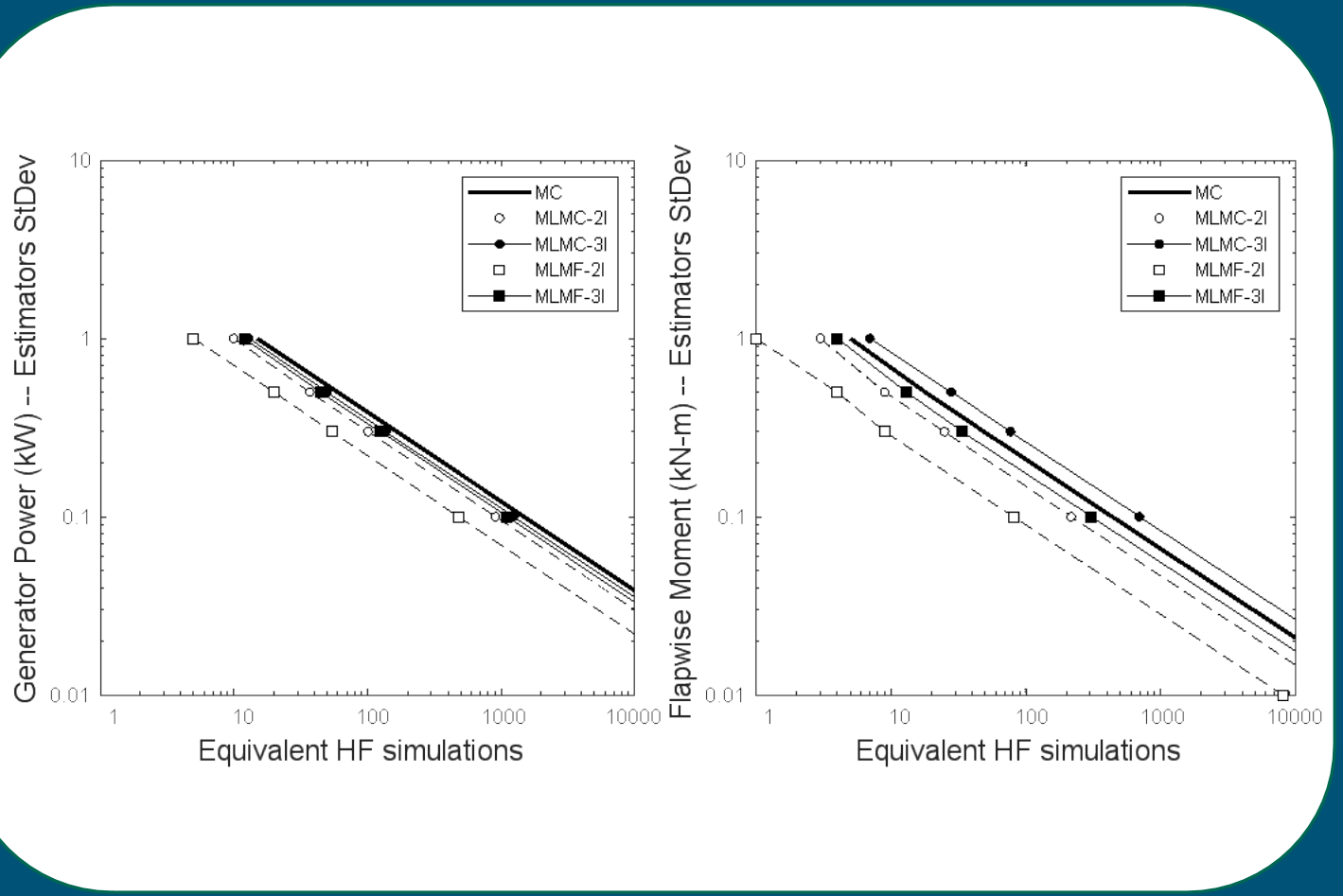
Present Results and Comparison to Previous Work

Comparison of estimator variance convergence between present results and Hsieh et al. (2020)

- Both the present study and Hsieh et al. (2020) generally show MLMF > MLMC > MC
- For both studies, MLMF-2I was the most efficient sampling strategy

MLMF strategies consistently perform the best even with completely different QoI relationships between the model levels

- In present study, MLMC results are significantly less efficient due to frequent non-convergence of the model levels
- The present third level (3I) results are less efficient than before due to Nalu ADC having a closer cost relationship with Nalu ADF
- Despite the present Nalu results having much different bias to the OpenFAST results than before, MLMF remains very effective in reducing cost



Conclusions

MLMF methods continue to demonstrate higher efficiency than MC/MLMC methods

- The best performing sampling strategy being MLMF shows agreement with both previous UQ studies in Maniaci et al. (2018) and Hsieh et al. (2020)
- Despite a significant change in the bias of the Nalu results compared to Hsieh et al. (2020), the lower-fidelity OpenFAST simulations were again well-correlated and provided significant variance reduction in MLMF strategies

A better mid-fidelity model in the current UQ workflow is necessary for MLMF strategies to be optimized

- The optimal sampling strategy being MLMF-2l for both the present study and Hsieh et al. (2020) shows adding the third level (Nalu ADC results) is consistently not beneficial due to the similar computational costs between Nalu ADC and Nalu ADF

Future Research

Development of URANS capability in Nalu-Wind and incorporate within MLMF framework

- Currently under development, expected completion in 2021.
- Offers a better mid-fidelity model within Nalu-Wind with computational costs more distinct from the OpenFAST-only and Nalu-Wind actuator simulations

Next major MLMF UQ study

- Abstract submitted to the 2021 Wake Conference in Visby, Sweden
- Expand UQ problem from single turbine to multiple turbines and wake effects
- In addition to pilot study, conduct second production UQ study to validate pilot results
- Add FAST.Farm and WindSE computational models to UQ workflow

References

Hsieh, A., Maniaci, D., Herges, T., Geraci, G., Seidl, D.T., Eldred, M., Blaylock, M., and Houchens, B. “Multilevel Uncertainty Quantification Using CFD and OpenFAST Simulations of the SWiFT Facility.” *2020 AIAA SciTech Forum.* 6-10 Jan. 2020, Orlando, Florida, 2020.

Maniaci, D., Frankel, A., Geraci, G., Blaylock, M., and Eldred, M. "Multilevel Uncertainty Quantification of a wind turbine large eddy simulation model." *7th European Conference on Computational Fluid Dynamics (ECFD 7)* 11-15 June 2018, Glasgow, UK, 2018.

Geraci, G. and Eldred, M. and Iaccarino, G. "A multifidelity control variate approach for the multilevel Monte Carlo technique." *CTR Annu. Res. Briefs*. pp. 169-181, 2015.

Geraci, G., Eldred, M., Gorodetsky, A. and Jakeman, J. "Recent advancements in Multilevel-Multifidelity techniques for forward UQ in the DARPA Sequoia project." *AIAA SciTech 2019 Forum*, 2019.

Pasupathy, R., Taaffe, M., Schmeiser, B. W. & Wang, W. "Control-variate estimation using estimated control means." *IIE Transactions*, vol. 44(5), pp. 381-385, 2014.

Peherstorfer, B., Willcox, K., Gunzburger, M. "Optimal model management for multifidelity Monte Carlo estimation." *SIAM Journal on Scientific Computing*, vol. 38(5), A3163A3194, 2016.

Gorodetsky, A. and Geraci, G. and Eldred, M. and Jakeman, J. "A Generalized Approximate Control Variate Framework for Multifidelity Uncertainty Quantification." arXiv preprint arXiv:1811.04988v3, 2018.