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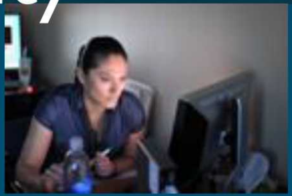
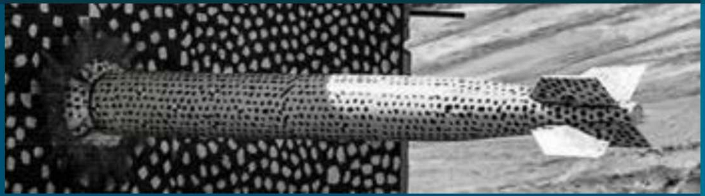
SAND2020-0179C

Multilevel Uncertainty Quantification Using CFD and OpenFAST Simulations of the SWiFT Facility





PRESENTED BY

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Presentation Overview

Motivation and Multifidelity UQ

Motivation

- Uncertainty quantification (UQ) is necessary for predictive wind simulations
- High-fidelity (HF) simulations are needed for accurate wind farm predictions
- For many applications, UQ for HF simulations with large numbers of uncertain parameters requires unattainable computational resources
- Multifidelity UQ helps mitigate the computational cost

Multifidelity UQ

- Aggregation of several lower accuracy models with handful of higher-fidelity computations
- Surrogate-based and sampling-based approaches
- Multilevel Monte Carlo (MLMC) approaches use 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) to decrease variance using model correlations and reduce stochastic errors

Motivation and Multifidelity UQ

Research Scope: Evaluation of MLMF UQ methods to improve predictive capabilities of computational models for wind farm applications

Types of UQ methods

- **Forward UQ**
- Inverse UQ
- Sensitivity Analysis
- Optimization under Uncertainty

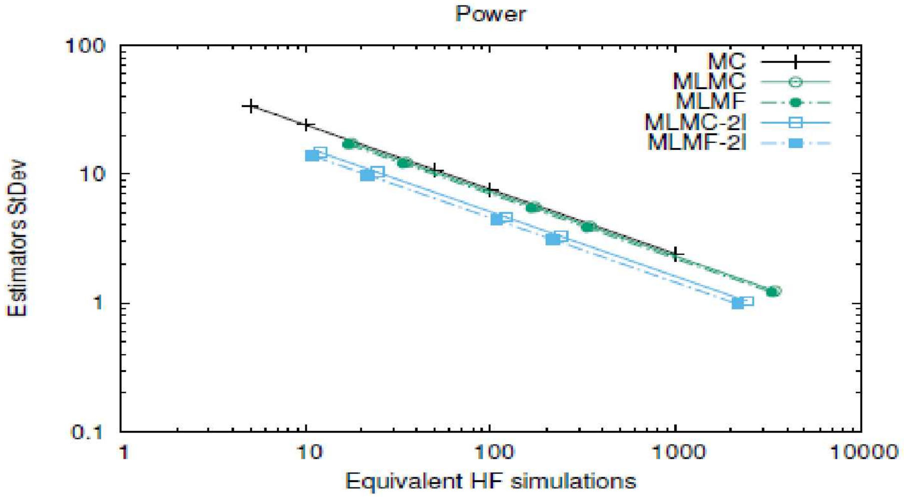
Previous Work:

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

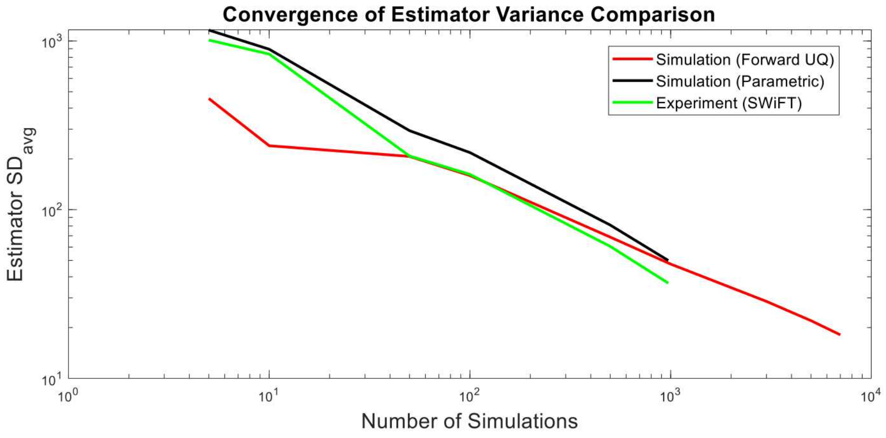
- Initial MLMF study using Nalu-Wind and OpenFAST

Hsieh, A.S. et al., "Continued Multilevel-Multifidelity Uncertainty Quantification of the SWiFT Wind Turbines." 2019 Wind Energy Science Conference. 2019.

- UQ comparison of OpenFAST simulations to experimental results from SWiFT site



(Maniaci et al., 2018)



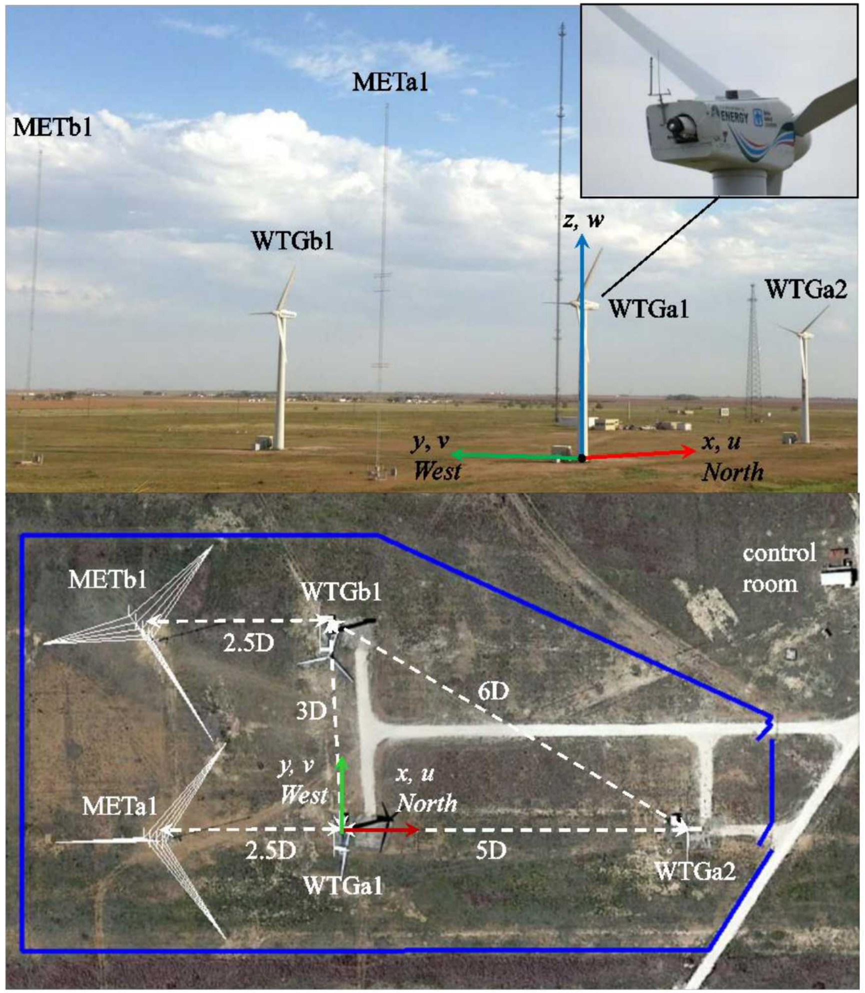
(Hsieh et al., 2019)

Presentation Overview

SWiFT Experimental Site

Scaled Wind Farm Technology (SWiFT) Facility

- Operated by Sandia National Laboratories in Lubbock, TX
- Three research-scale wind turbines and two meteorological towers
  - Vestas V27 wind turbine blades
  - DTU SpinnerLidar to measure wake planes downstream of WTGa1 turbine
- High-quality measurement data for uncertainty characterization of atmospheric inflow parameters, turbine parameters and wake characteristics
- Open-source information and data repository at the A2e Data Archive Portal (DAP): https://a2e.energy.gov/projects
  - Mesoscale-Microscale Coupling Experiment (MMC). March 2015 – Sept. 2018
  - Wake Steering Experiment (WAKE). Dec. 2016 – July 2017.



SWiFT site layout and coordinate system.
D = 27 m

Presentation Overview

- Motivation and Multifidelity UQ
- SWiFT Experimental Site
- MLMF Sub-Models Overview
- MLMF Sampling Strategies
- Sampling Study Overview and Results
- Conclusions and Future Research

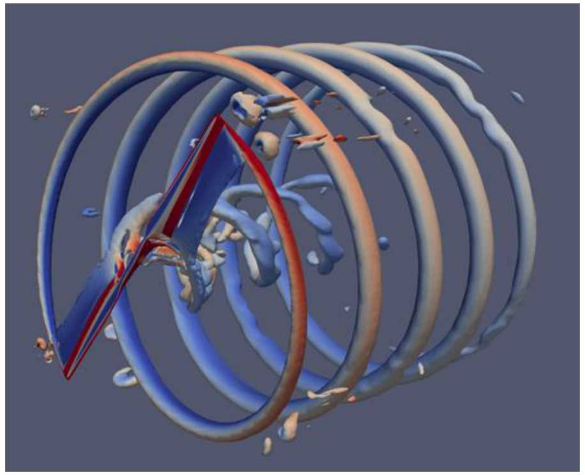
MLMF Sub-Models Overview

Nalu-Wind

- Massively parallel, open source large eddy simulation code (LES) used to simulate the atmospheric boundary layer
- One-equation, constant coefficient, turbulent kinetic energy (TKE) model used for the subgrid scale stresses
- Actuator disk, actuator line and blade-resolved methods to model wind turbines

OpenFAST

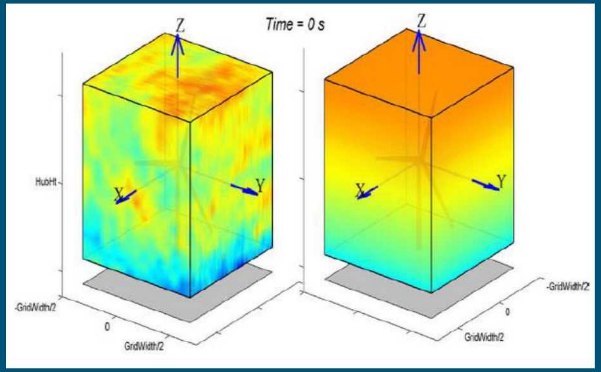
- Open-source tool suite used to simulate the coupled dynamic response of wind turbines
- Modular framework to model different physical dynamics
  - AeroDyn: Turbine aerodynamics
  - ElastoDyn: Turbine structural dynamics
  - ServoDyn: Turbine control and electrical drive dynamics



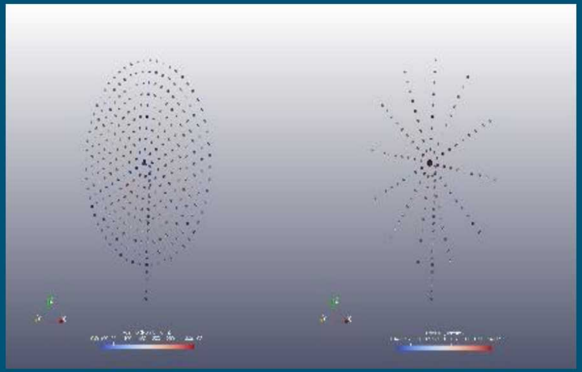
Visualization of blade-resolved Nalu-Wind simulation

MLMF Sub-Models Overview

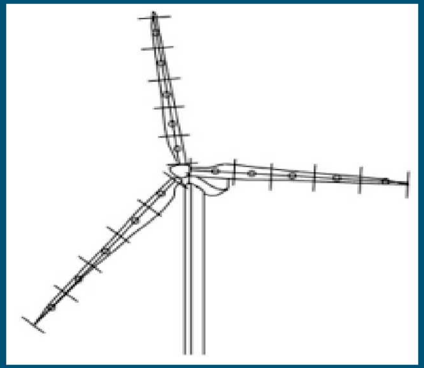
Multilevel-Multifidelity sampling requires selection of varying model fidelities



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: Turbine dynamics model

Mid-fidelity model

- Nalu-Wind Actuator Disk (Nalu-AD) + OpenFAST
- Constant body-force applied over entire rotor

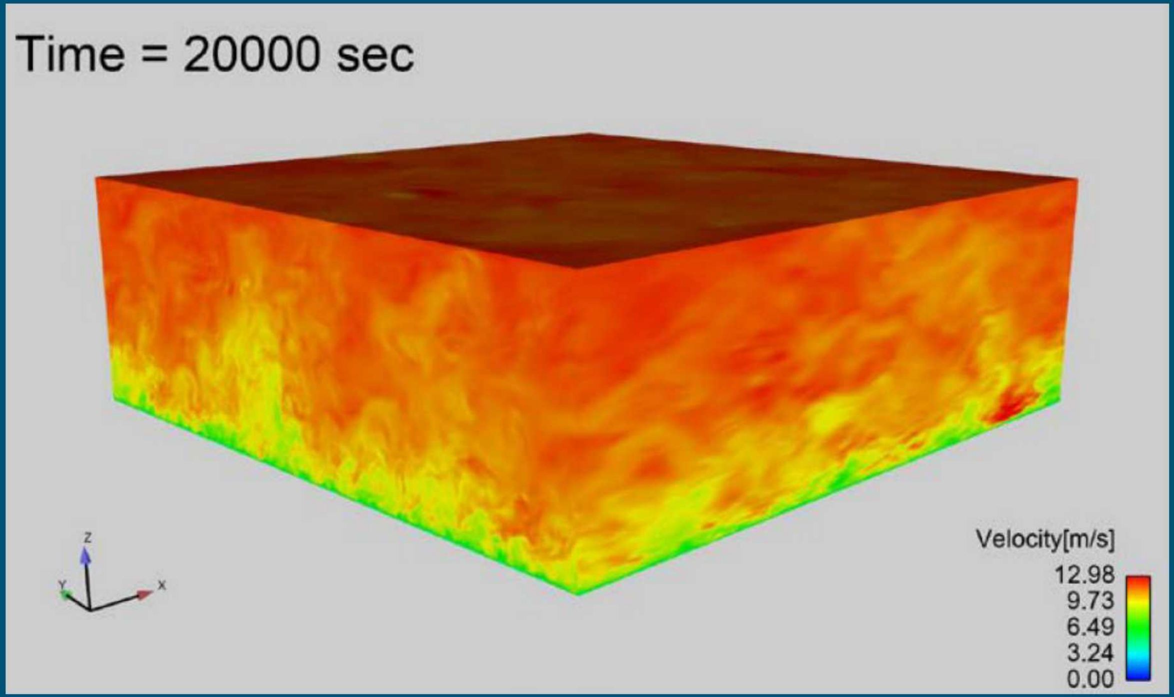
High-fidelity model

- Nalu-Wind Actuator Line (Nalu-AL) + OpenFAST
- Body-forces applied over blade-like lines

MLMF Sub-Models Overview

Nalu-Wind + OpenFAST Workflow

- **Stage 1: ABL Precursor**
  - **Periodic BCs**
  - **Uniform 10 m resolution mesh**
  - **Runtime of 20,000 seconds for well-developed turbulent flow field**
  - **Neutral ABL; hub-height wind speed: 8.69 m/s**
- Stage 2: ABL Precursor + I/O Plane
  - Periodic BCs
  - Uniform 10 m resolution mesh
  - Runtime of 630 seconds to provide I/O planes
- Stage 3: Turbines w/ ABL
  - Inflow/outflow BCs
  - Refined meshes around turbines
  - Runtime of 630 seconds to simulate wind turbines (First 30 seconds discarded to avoid initial start-up transience for statistics)



MLMF Sub-Models Overview

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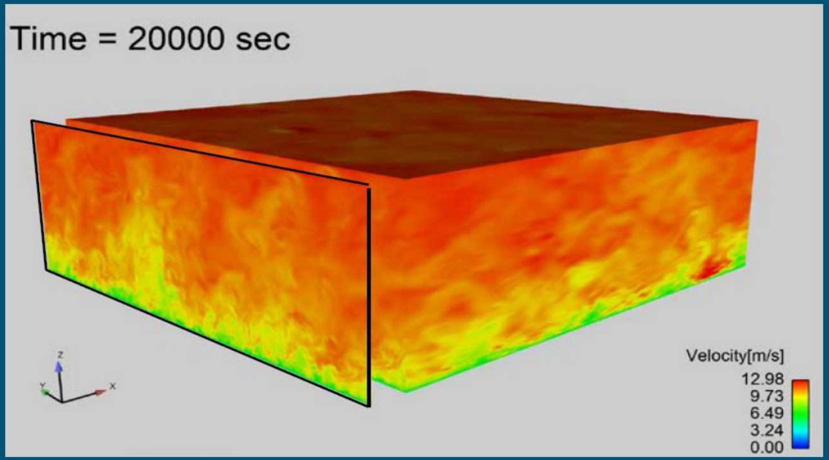

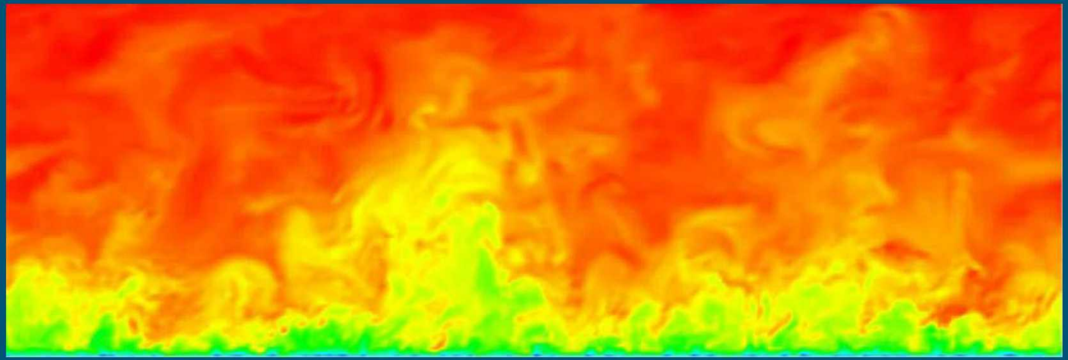

MLMF Sub-Models Overview

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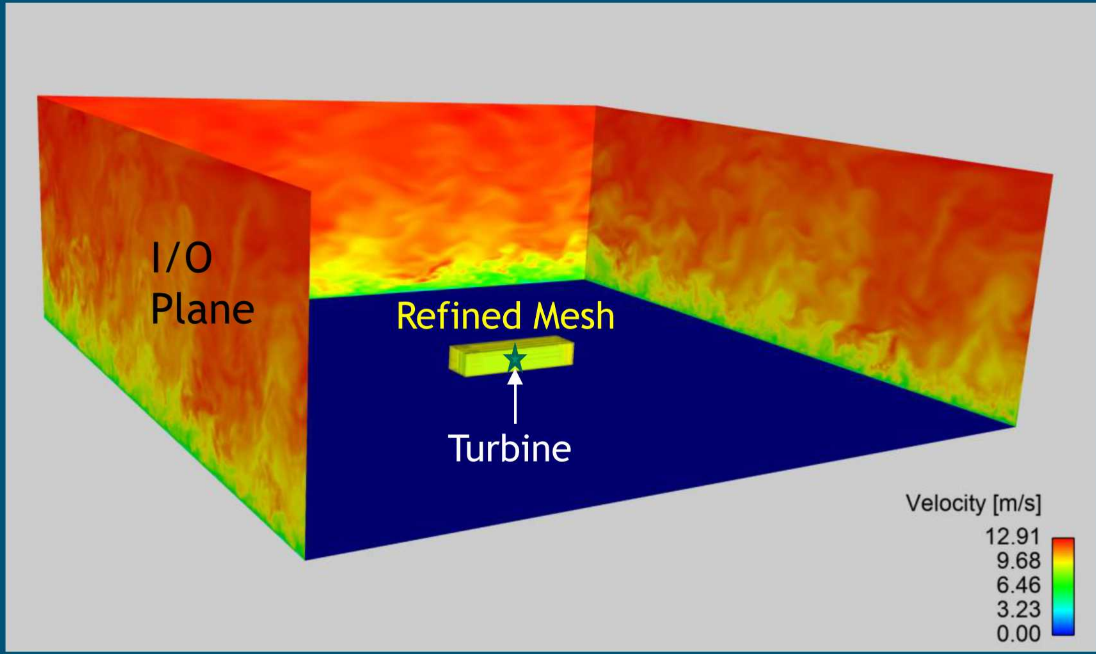


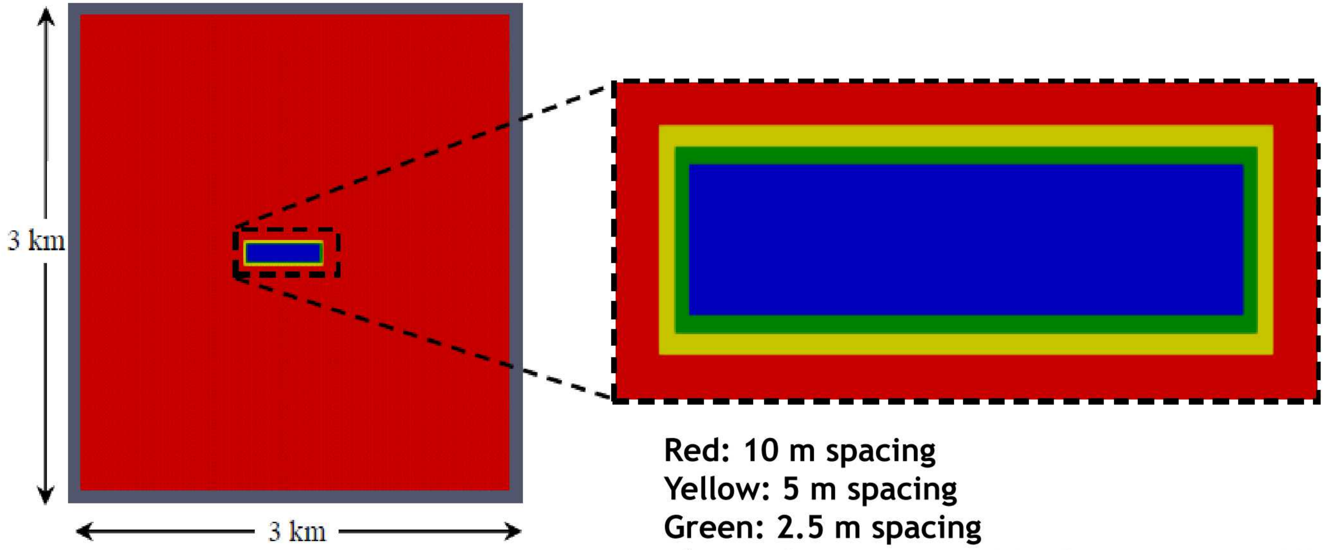
MLMF Meshes Overview

Coarse "C" mesh

- 3 km x 3 km x 1 km
- 9.5 million elements
- Two refinement levels
- Minimum grid spacing: 2.5 m

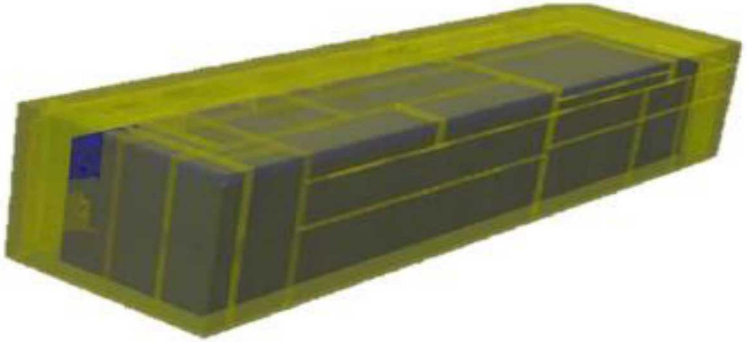
Fine "F" mesh

- 3 km x 3 km x 1 km
- 11.7 million elements
- Three refinement levels
- Minimum grid spacing: 1.25 m



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

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



3D perspective view of two refinement regions

Presentation Overview

MLMF Sampling Strategies

Single-level Monte Carlo (MC) Approach

- MC estimator $\hat{Q}_N^{MC}$ is reliable, unbiased and robust
- Method has slow rate of convergence
- Requires high number (N) of high-fidelity (HF) simulations

$$\hat{Q}_N^{MC} = \frac{1}{N}\sum_{i=1}^{N} Q\left(\xi^{(i)}\right) = \frac{1}{N}\sum_{i=1}^{N} Q^{(i)} \qquad \varepsilon^2 = Var\left[\hat{Q}_N^{MC}\right] = \frac{Var[Q]}{N}$$

MC estimator and variance

MLMF Sampling Strategies

Single-level Monte Carlo (MC) Approach

- MC estimator $\hat{Q}_N^{MC}$ is reliable, unbiased and robust
- Method has slow rate of convergence,
- Requires high number (N) of high-fidelity (HF) simulations

Multilevel Monte Carlo (MLMC) Approach

- MLMC estimator $\hat{Q}_L^{MLMC}$ is the sum of independent MC estimators Y_l for each level l
- MLMC performs sequential corrections using less accurate models (i.e. coarser spatial resolutions)
- Effective MLMC requires $Y_l \to 0$ for $l \to \infty$

$$\hat{Q}_N^{MC} = \frac{1}{N}\sum_{i=1}^{N} Q\left(\xi^{(i)}\right) = \frac{1}{N}\sum_{i=1}^{N} Q^{(i)} \qquad \varepsilon^2 = Var\left[\hat{Q}_N^{MC}\right] = \frac{Var[Q]}{N}$$

MC estimator and variance

$$Q_L = Q_0 + (Q_1 - Q_0) + \cdots + (Q_L - Q_{L-1})$$

$$Y_l = \begin{cases} Q_l - Q_{l-1} \text{ for } l > 0 \\ Q_0 \text{ for } l = 0 \end{cases}$$

Multilevel expansion of MC estimator

$$\hat{Q}_L^{MLMC} = \sum_{l=0}^{L} \frac{1}{N_l} \sum_{i=1}^{N_l} Y_l^{(i)}.$$

$$\varepsilon^2 = Var\left[\hat{Q}_L^{MLMC}\right] = \frac{Var[Y_0]}{N_0} + \frac{Var[Y_1]}{N_1} + \frac{Var[Y_2]}{N_2} + \cdots$$

MLMC estimator and variance

MLMF Sampling Strategies

Multilevel-Multifidelity (MLMF) Approach

- With different model fidelities, statistical convergence is unlikely
- MLMF relies on model correlations between fidelities instead of monotonically decaying variance
- A classical control variate estimator $\hat{Q}^{CV,HF}_{L,N_{HF}}$ approximates Q^{HF}_L by adding an unbiased term based on Q^{LF}_L
- The low-fidelity model's expected value, $\mathbb{E}[\hat{Q}^{LF}_{L,N_{LF}}]$, is approximated by adding a term Δ_{LF} to represent the additional number of low-fidelity simulations

$$\hat{Q}^{CV,HF}_{L,N_{HF}} = \hat{Q}^{HF}_{L,N_{HF}} + \alpha\left(\hat{Q}^{LF}_{L,N_{HF}} - \mathbb{E}[\hat{Q}^{LF}_{L,N_{LF}}]\right)$$

$$argmin_\alpha \, Var(\hat{Q}^{CV,HF}_{L,N_{HF}}) \longrightarrow \alpha = -\rho \frac{\sigma_{HF}}{\sigma_{LF}}$$

$$\rho = \frac{cov(Q^{HF}_L, Q^{LF}_L)}{\sigma_{HF}\sigma_{LF}}$$

MLMF Control Variate Estimator

$$\Delta_{LF} = rN_{HF}$$

$$N_{LF} = N_{HF} + \Delta_{LF} = N_{HF}(1+r)$$

$$\mathbb{E}[\hat{Q}^{LF}_{L,N_{LF}}] \simeq \frac{1}{(1+r)N_{HF}} \sum_{i=1}^{(1+r)N_{HF}} Q^{LF,(i)}_L$$

$$Var\left(\hat{Q}^{CV,HF}_{L,N_{HF}}\right) = Var\left(\hat{Q}^{HF}_L\right)\left(1 - \frac{r}{1+r}\rho^2\right)$$

MLMF variance

MLMF Sampling Strategies

Basic MLMC/MLMF Example

- Two Models: A and B. Model A is far more computationally expensive than Model B.
- Model A, Resolution 0 (A0)
- Model A, Resolution 1 (A1)
- Model A, Resolution 2 (A2)
- Model B, Resolution 0 (B0)
- Resolutions 0 → 2 in order of increasing resolution
- Models A and B have known correlations but unknown convergence
- MLMF reduces the number of high-fidelity simulations for the level on which the control variate is applied

MLMC-3l

$A2\ (Q_2)$
$A1\ (Q_1)$ $\to Y_2 = Q_2 - Q_1$

$A1\ (Q_1)$
$A0\ (Q_0)$ $\to Y_1 = Q_1 - Q_0$

$A0\ (Q_0) \to Y_0 = Q_0$

Number of Sim.

	Model A	Model B
Res. 0	1,000	0
Res. 1	100	0
Res. 2	10	0

MLMF-3l

$A2\ (Q_2)$
$A1\ (Q_1)$ $\to Y_2 = Q_2 - Q_1$

$A1\ (Q_1)$
$A0\ (Q_0)$ $\to Y_1 = Q_1 - Q_0$

$A0\ (Q_0) \leftrightarrow B0(Q_{LF}) \to$
$Y_0 = Q_0 + \alpha(Q_{LF} - \mu_{LF})$

Number of Sim.

	Model A	Model B
Res. 0	200	10,000
Res. 1	100	0
Res. 2	10	0

MLMF Sampling Strategies

1. Target accuracy for estimator: ε
   - Calculate optimal # of simulations per level
   - Uncertain total computational cost

2. $N_L = N_{target}$
   - Fixed # of highest-level model simulations
   - Calculate optimal # of simulations for lower levels
   - Uncertain estimator accuracy

MC

$$N_0 = \frac{Var[Q]}{\varepsilon^2}$$

MLMC

$$N_l = \frac{1}{\varepsilon^2} \sum_{k=0}^{L} \sqrt{\mathbb{V}ar(Y_k) C_k} \sqrt{\frac{\mathbb{V}ar(Y_l)}{C_l}}$$

MLMF

$$N_l = \frac{1}{\varepsilon^2} \sum_{k=0}^{L} \sqrt{\mathbb{V}ar(Y_k) C_k^{eq} \Lambda_k} \sqrt{\frac{\mathbb{V}ar(Y_l)\Lambda_l}{C_l^{eq}}}$$

Optimal # of simulations per level for given variance

$$C = C_0 N_0$$

$$C = \sum_{l=0}^{L} C_l N_l$$

$$C_l^{eq} = C_l^{HF} + (1 + r_l) C_l^{LF}$$

Total simulation computational cost for given # of realizations

Presentation Overview

Sampling Study Overview

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-AD C	7	768	5,376	21,504
Nalu-Wind + AD fine	Nalu-AD F	16.5	768	12,672	50,688
Nalu-Wind + AL fine	Nalu-AL F	31.75	768	24,384	97,536

Sampling Method Descriptions

Category	Sampling Method	Sub-Models
MC	MC	Nalu-AL F
MLMC	MLMC-2l	Nalu-AL F, Nalu-AD F
	MLMC-3l	Nalu-AL F, Nalu-AD F, Nalu-AD C
MLMF	MLMF-2l	Nalu-AL F, Nalu-AD F, OpenFAST
	MLMF-3l	Nalu-AL F, Nalu-AD F, Nalu-AD C, OpenFAST

Sampling Study Overview

Five aleatoric uncertain turbine inputs

- Lower and upper bounds were informed by experimental data from SWiFT site

Four quantities of interest (QoIs): 10-min means

- Generated power
- Rotor thrust
- Flapwise blade-root bending moment
- Edgewise blade-root bending moment

Sandia-based Dakota UQ tool used to generate samples

Differences from initial MLMF study (Maniaci et al., 2018)

- Three uncertain inputs: wind speed, yaw offset and air density
- Two QoIs: Generated power and rotor thrust
- Two model fidelities: OpenFAST and Nalu-AL
- No ABL precursor and uniform, low resolution meshes for Nalu-Wind
- Present Nalu-Wind UQ simulations offer similar fidelity to benchmark-level ABL simulations

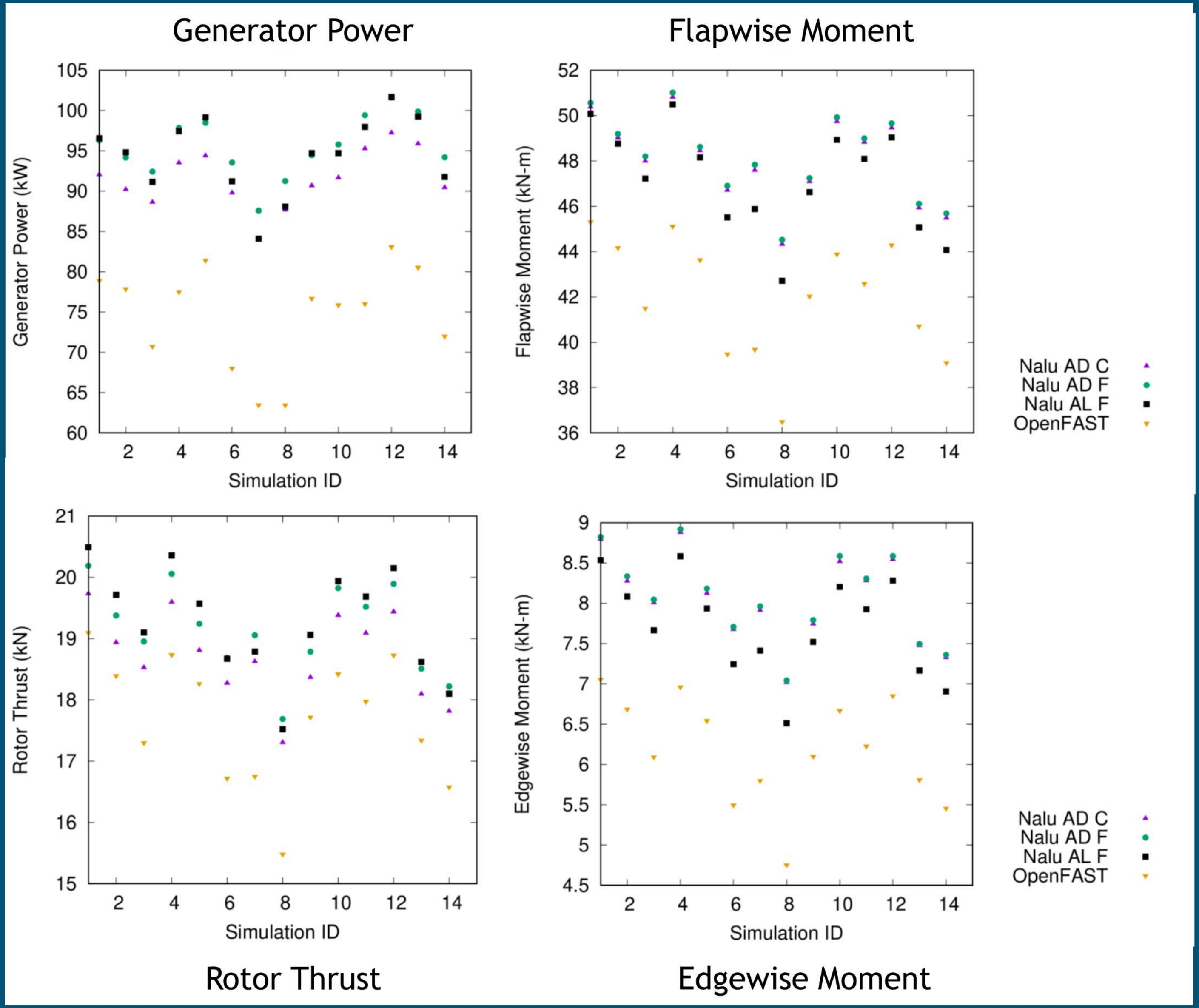
Sampling Study Aleatoric Uncertain Inputs

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

Sampling Study Results

Computed values from sampling study simulations

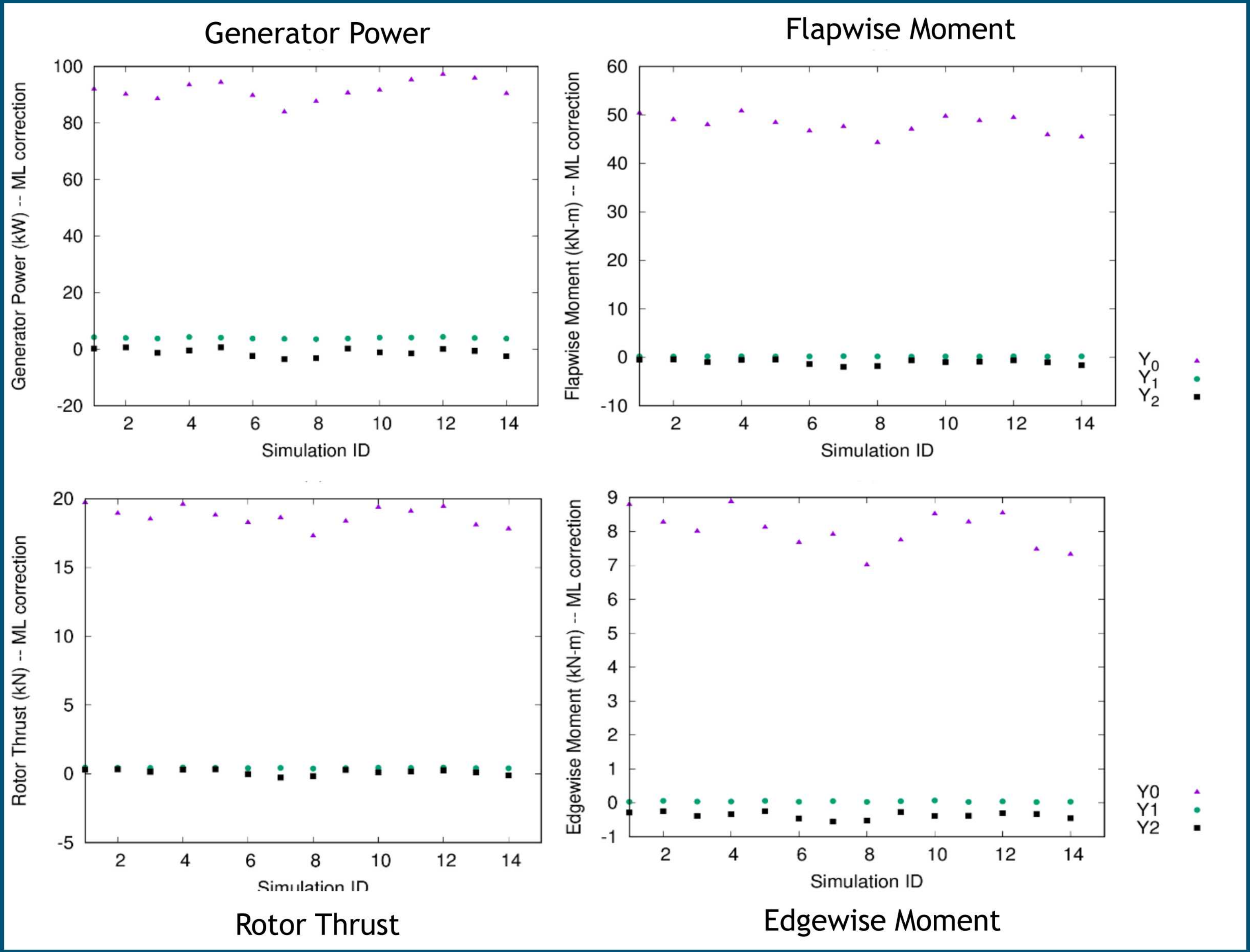
- ➢ OpenFAST under-predicts QoIs between 10-50% compared to Nalu-Wind
- ➢ Increasing mesh resolution for Nalu-AD leads to higher QoI predictions
- ➢ Correlation between Nalu-AL and Nalu-AD results varies between QoIs



Sampling Study Results

Multilevel corrections (MLMC-3l) from sampling study simulations

- ➢ MLMC condition of $Y_l \rightarrow 0$ for $l \rightarrow \infty$ is generally satisfied
- ➢ Rotor thrust and flapwise moment display weakly monotonic convergence of Y_l



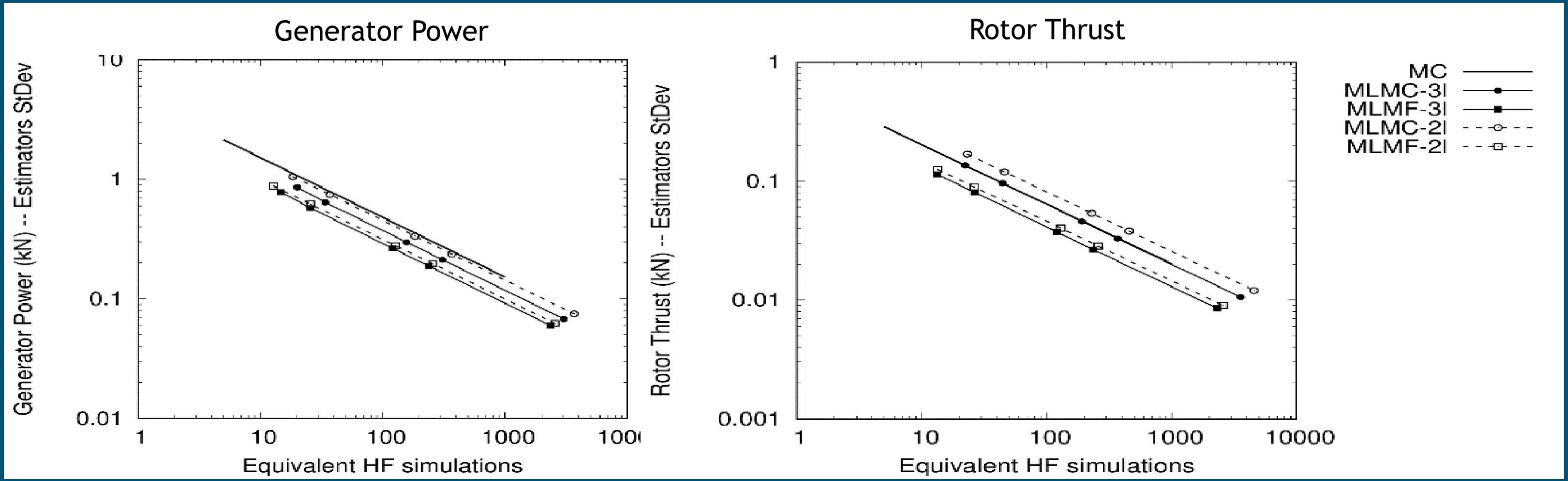
ML Correction Glossary

- ➢ Y_0: Nalu AL F – Nalu AD F
- ➢ Y_1: Nalu AD F – Nalu AD C
- ➢ Y_2: Nalu AD C

Sampling Study Results

Extrapolated estimator performance for generator power and rotor thrust

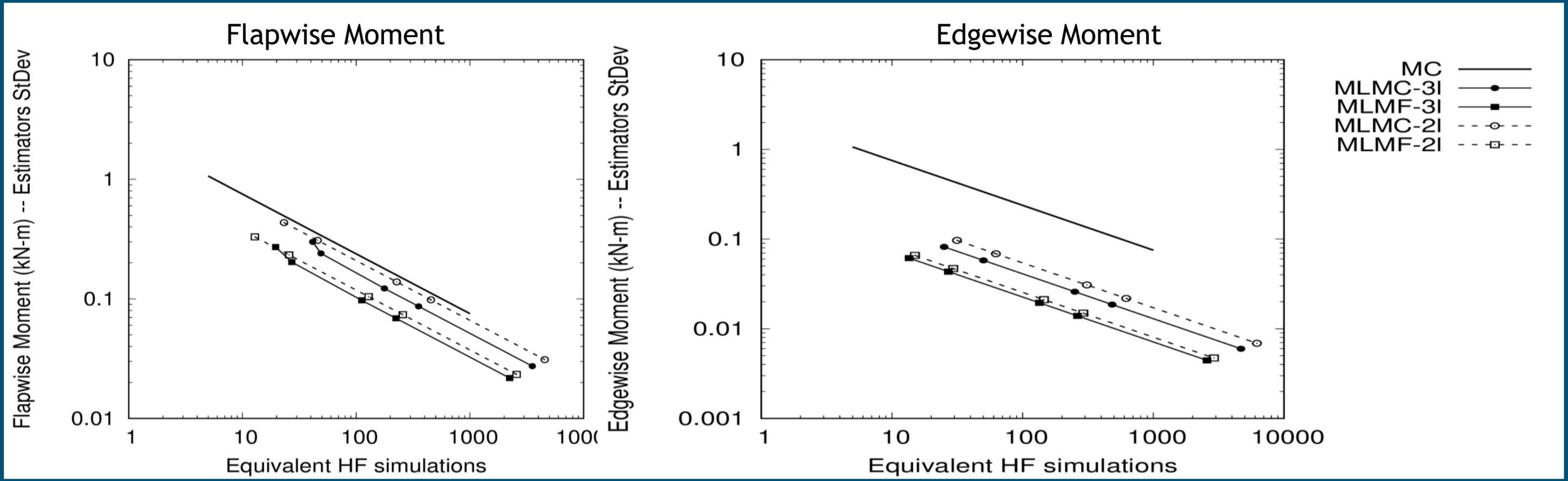
- Lower estimator StDev indicates higher reliability of sampling method
- Generator Power (least to most reliable): MC, MLMC-2l, MLMC-3l, MLMF-2l, MLMF-3l
- Rotor Thrust (least to most reliable): MLMC-2l, MC/MLMC-3l, MLMF-2l, MLMF-3l



Sampling Study Results

Extrapolated estimator performance for flapwise and edgewise bending moments

- ➢ Flapwise Moment (least to most reliable): MC, MLMC-2l, MLMC-3l, MLMF-2l, MLMF-3l
- ➢ Edgewise Moment (least to most reliable): MC, MLMC-2l, MLMC-3l, MLMF-2l, MLMF-3l
- ➢ Order of sampling method efficiency is consistent among QoIs with exception of rotor thrust



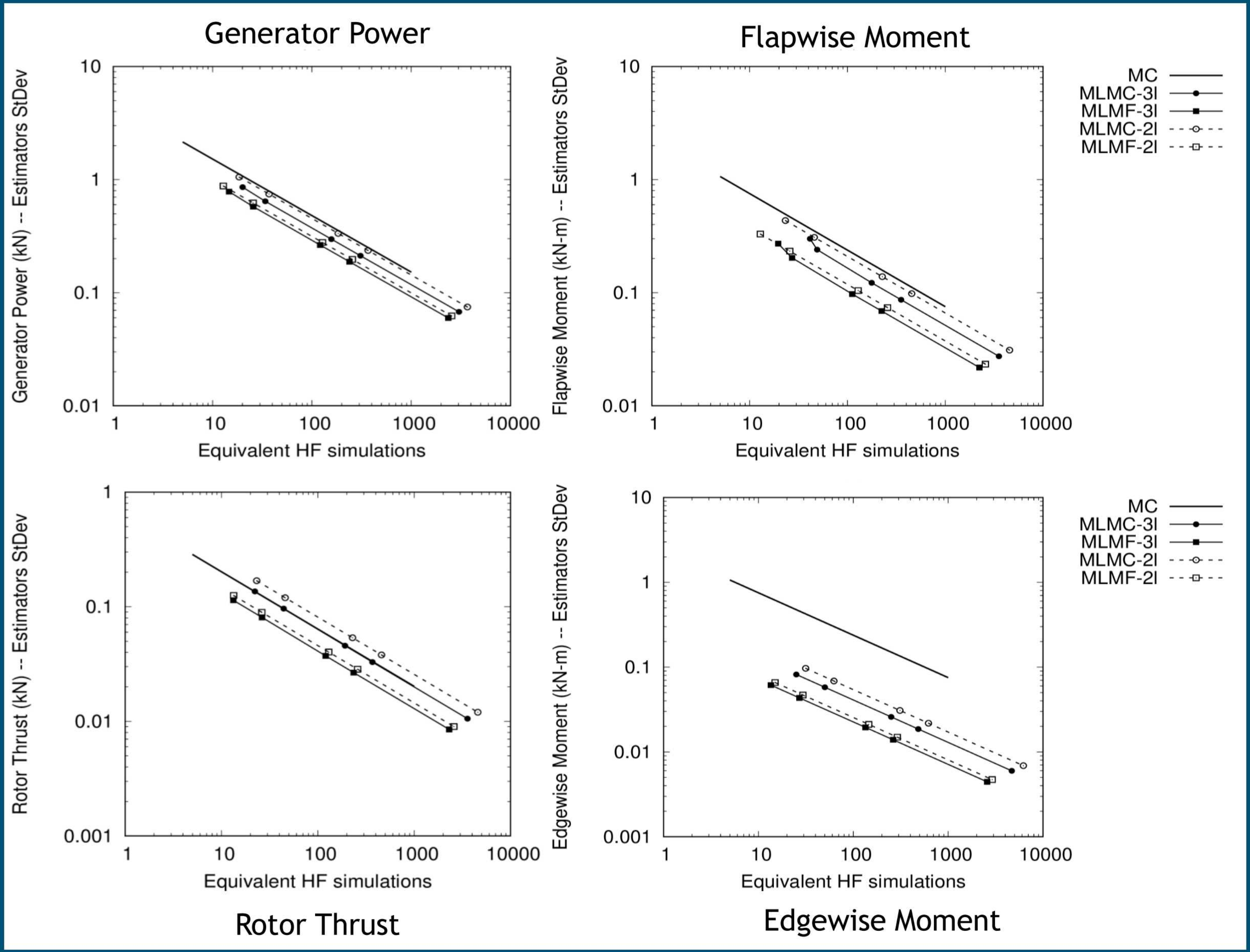
Sampling Study Results

General sampling method performance is consistent

- MLMF > MLMC > MC for all QoIs except rotor thrust
- Poor performance of MLMC for rotor thrust may be attributable to weakly monotonic decay of Y_l

Relative estimator efficiency improvements between sampling methods vary significantly by QoI

- Edgewise moment estimator performance is improved dramatically by MLMC and MLMF methods
- Generator power estimator performance improvements are small for MLMC and MLMF methods
- Control variate usage with OpenFAST model (MLMC → MLMF) is generally more effective than adding a resolution level (2l → 3l)



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Conclusions and Future Research

Conclusions

MLMF methods consistently demonstrate higher efficiency than MC/MLMC methods

- High MLMF efficiency shows agreement with previous MLMF study (Maniaci et al., 2018)
- Edgewise bending moment shows greatest improvement for MLMF methods
- OpenFAST is an effective low-fidelity simulation tool for power, thrust and bending moments

Third-level sampling strategies consistently demonstrate higher efficiency than second-level sampling strategies

- Previous MLMF study (Maniaci et al., 2018) showed second-level sampling methods were more reliable than third-level sampling methods

MLMF methods demonstrated greater consistency of effectiveness than MLMC methods

- MLMC methods showed poor performance for rotor thrust
- Weakly monotonic convergence of $Y_l \rightarrow 0$ for $l \rightarrow \infty$ may result in ineffective MLMC applications

Future Research

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

- Offers additional mid-fidelity model within Nalu-Wind

Look at more complex, higher-order QoIs

- Damage equivalent loads (DEL)

MLMF UQ study for ABL parameters

- Validation of newly implemented BC changes in Nalu-Wind for convective and stable ABL simulations

MLMF UQ study for turbine wake characteristics

- FAST.Farm and WindSE computational wind farm models

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