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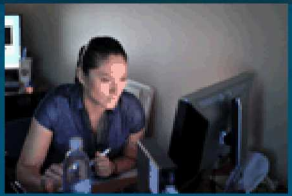
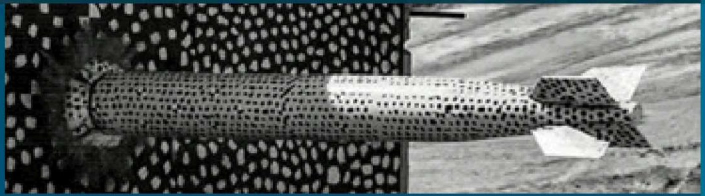
Continued Multilevel-Multifidelity Uncertainty Quantification of the SWiFT Wind Turbines





PRESENTED BY

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Presentation Overview

Research Motivation and Overview

The prediction of wind energy is a stochastic forcing problem, built upon randomness and uncertainty

Evaluate the potential for Multilevel-Multifidelity (MLMF) Uncertainty Quantification (UQ) methods to improve the predictive capabilities of computational models

Scope: Multilevel-Multifidelity Uncertainty Quantification of Wind Farms

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

- Multilevel-Multifidelity study (MLMF) using Nalu-Wind and OpenFAST (3 mesh levels and 2 model fidelities)

- Demonstrated significant improvement in estimator efficiency compared to standard Monte-Carlo methods

Robertson, A. et al. "Assessment of Wind Parameter Sensitivity on Extreme and Fatigue Wind Turbine Loads." *36th Wind Energy Symposium*. American Institute of Aeronautics and Astronautics, 2018.

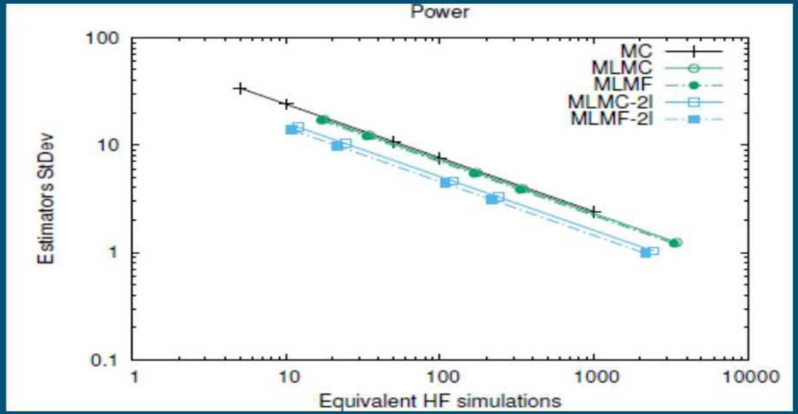
- Sensitivity analysis of 18 atmospheric inflow parameters on turbine fatigue loads

- Most sensitive parameters included shear, turbulence standard deviation in wind direction

ECCOMAS Models, Parameters and Results

Case	Mesh size	Simulation time (sec)	CPUs	Cost (CPU-hours)	Cost (relative)
OpenFAST		500	1	0.42	1
Coarse	100x50x50	2000	80	240	576
Medium	200x100x100	2000	160	960	2304
Fine	400x200x200	2000	400	6860	16500

Uncertainty	Minimum	Maximum
Speed	6.5 m/s	7.5 m/s
Density	0.97 kg/m^3	1.19 k/m^3
Yaw	-25°	25°



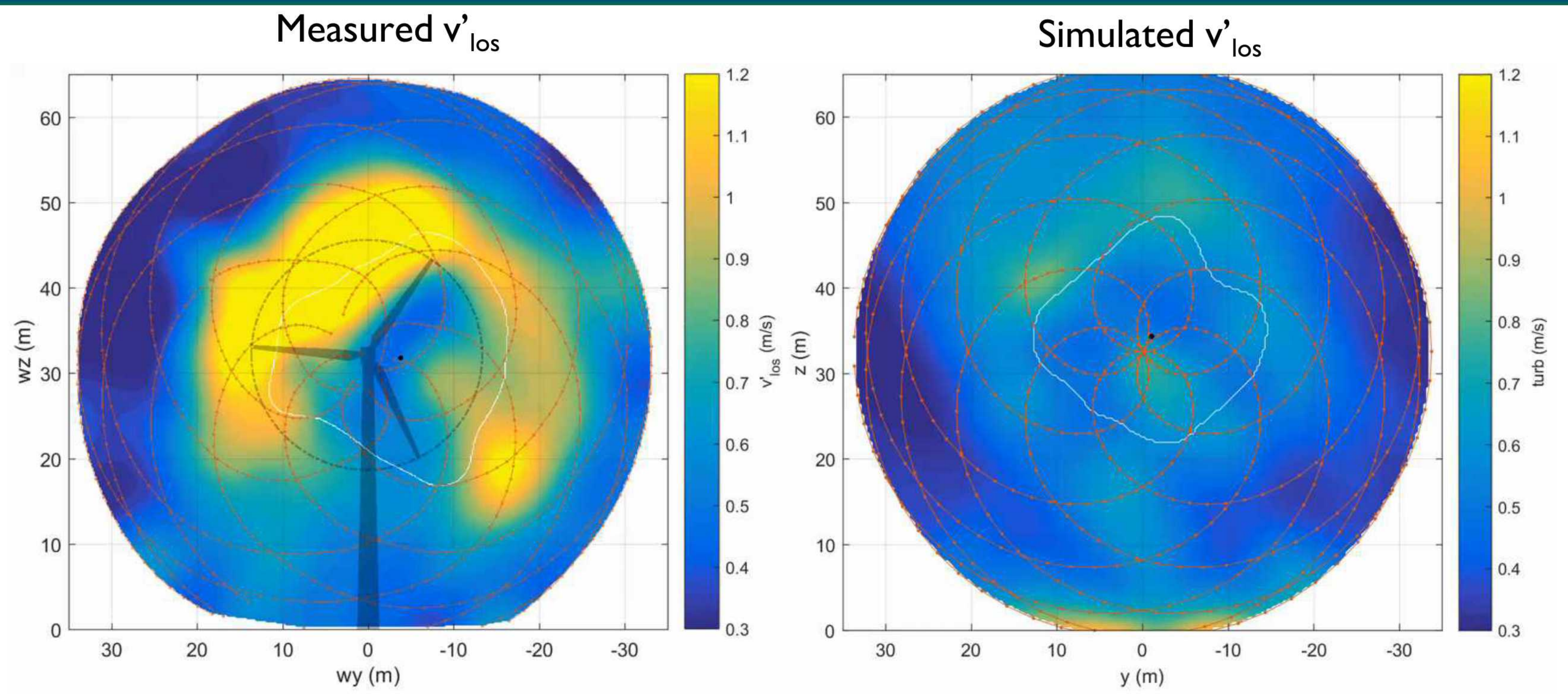
Research Motivation and Overview

Research Motivation and Objectives

- Utilize experimental data to inform simulation model inputs
- Compare uncertainty, estimator variance and convergence rate between simulation and experiment

Scope: IEA Task 31: Verification & Validation and Uncertainty Quantification

- Uncertainty quantification can better inform the high-fidelity model validation process by reducing estimator variance and identifying the most sensitive parameters within models



MLMF Models Overview and Hierarchy

Estimator Variance (Mean Square Error) = Sampling error (stochastic error) and residual bias (deterministic error)

$\hat{Q}^{MC}_{M,N} = \frac{1}{N}\sum_{i=1}^{N} Q_M^{(i)}$ $\quad E\left[\left(\hat{Q}^{MC}_{M,N} - E[Q]\right)^2\right] = N^{-1}Var(Q_M) + (E[Q_M - Q])^2$

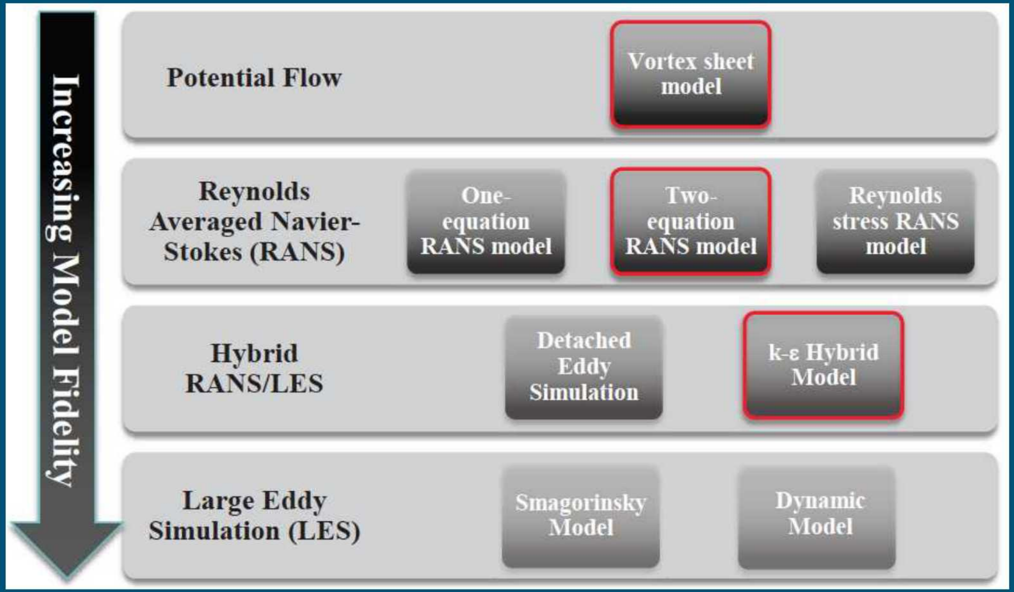
Multilevel-Multifidelity methodology determines the optimal resource allocation within a hierarchy of models for a limited computational budget to reduce estimator variance

Definitions

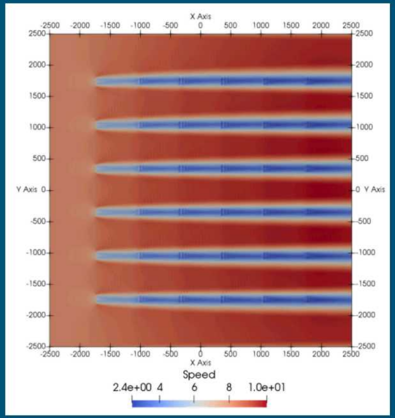
- Multifidelity refers to phenomenon characterization and closure approximations
- Multilevel refers to discretization levels and resolution controls

Strategy

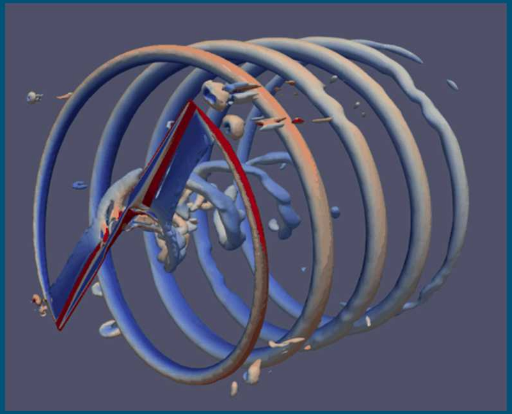
- Resource allocation is informed by model correlations and relative computational model costs
- Utilize all model results in a collective fashion. Do not 'inform then neglect'.



Model Fidelity Chart (Eldred, M. S.)



WindSE



Nalu-Wind Blade Resolved

MLMF Models Overview and Hierarchy

Model Hierarchy Nalu-Wind

-Open-source LES code with actuator line/disc models and blade-resolved capability

WindSE

-2D/3D RANS model simulation code for complex terrain

OpenFAST-AeroDyn-TurbSim

-Wind turbine simulation model using Blade-Element/Momentum (BEM) theory

FAST.Farm

-Wind farm-scale simulation model for multiple turbine configurations

MLMF Model Hierarchy and Computational Cost Chart

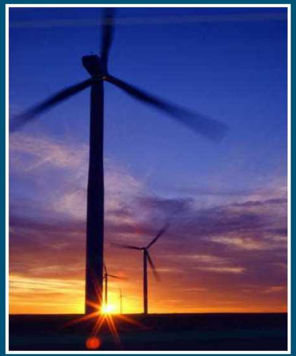
Model	Modeled Physics		Mesh Size	CPUs	Computational Cost (core-hours)	Run Time (hrs)
	Power	Loads				
Empirical Wake Model	x		-	1	0.1	0.1
OpenFAST-AeroDyn+TurbSim		x	-	1	0.25	0.25
FAST.Farm w/o ABL		x	-	2	1	0.5
Vortex Method Free Wake	x	x	0.1e6	16	384	24
Nalu-Wind Actuator Disc	x	x	11.7e6	768	7,700	10
Nalu-Wind Actuator Line						
Coarse	x	x	11.7e6	768	23,000	30
Medium	x	x	22.4e6	768	48,000	63
Fine	x	x	40.8e6	768	108,000	140

SWiFT Experiment Overview and UQ

Scaled Wind Farm Technology Facility (SWiFT)

- Ability to characterize the uncertainty of atmospheric inflow parameters, turbine parameters and wake characteristics

- Open-source information and data repository (A2e: Data Archive Portal)



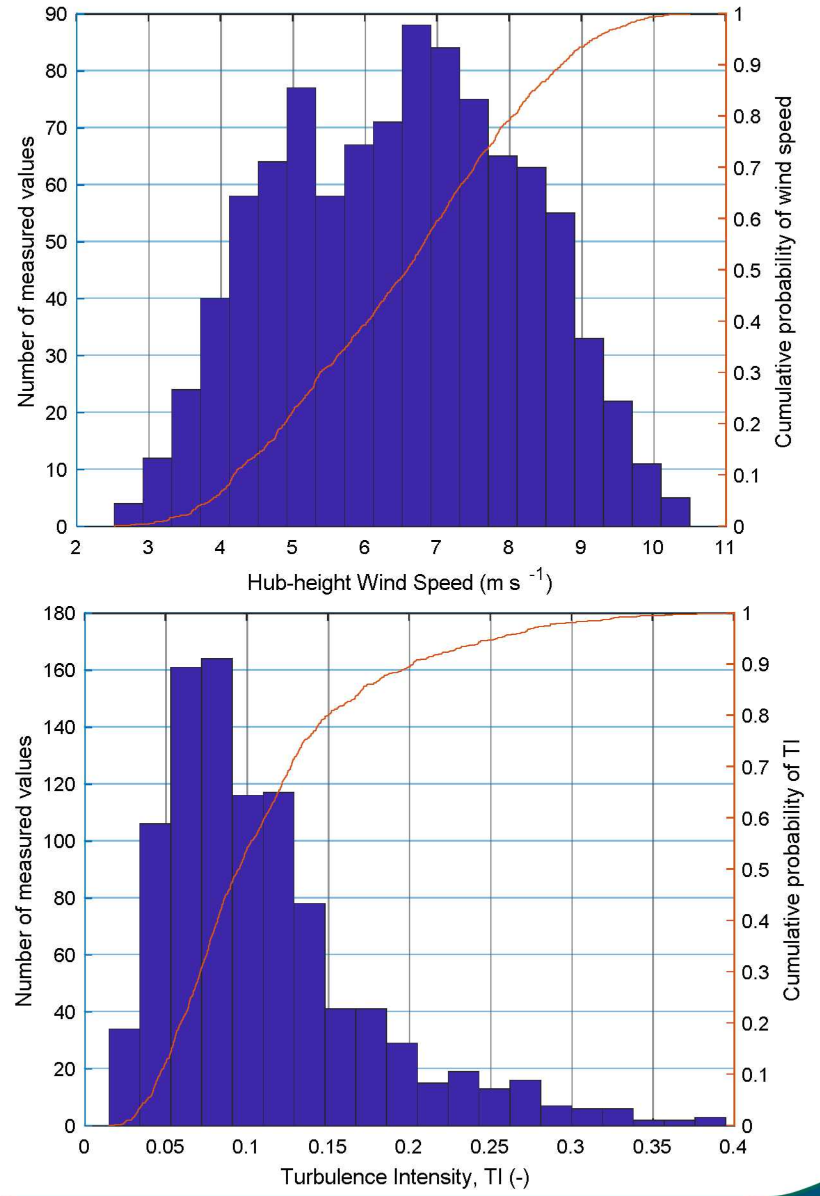
- Inflow Measurements
  - α
  - ρ
  - p
  - RH
  - T
  - TI (sonic)
  - U_∞ (sonic)
  - U (sonic)
  - V (sonic)
  - U_∞ (cup)
  - U_∞ (nacelle)
  - Vr (sonic)
  - WD (sonic)
  - WD (vane)
- Turbine Measurements
  - Aerodynamic power
  - Rotor speed
  - Aerodynamic torque
  - Rotor thrust
  - Individual blade root loads (instantaneous)
  - Individual blade loading profile (instantaneous)
  - Nacelle measured wind direction
  - Nacelle measured wind speed
  - Yaw heading
  - Yaw misalignment
  - Blade pitch
  - Rotor azimuth
  - Nacelle acceleration
- Wake Measurements
  - DTU Spinner Lidar
  - Wake identification and tracking
  - Turbulence estimators

SWiFT Experiment Overview and UQ

List of measured experimental values

Measurand	units	u	u/mean (%)	mean
α	-	1.88×10^{-3}	0.89	0.21
ρ	kg/m^3	7.9×10^{-4}	0.0731	1.08
p	Pa	1.53	1.71×10^{-3}	89500
RH	%	2.01	4.49	46.8
T	K	0.212	0.0733	289
TI (sonic)	-	1.23×10^{-3}	1.02	0.12
U_∞ (sonic)	m/s	0.0439	0.207	6.82
U (sonic)	m/s	0.01	0.207	4.82
V (sonic)	m/s	0.01	0.207	4.82
U_∞ (cup)	m/s	0.20	2.93	6.82
U_∞ (nacelle)	m/s	0.50	7.33	6.82
Vr (sonic)	°	1.75	86	2.0
WD (sonic)	°	1.22	0.69	176
WD (vane)	°	1.20	0.68	176

Bin and cdf distributions from experimental data

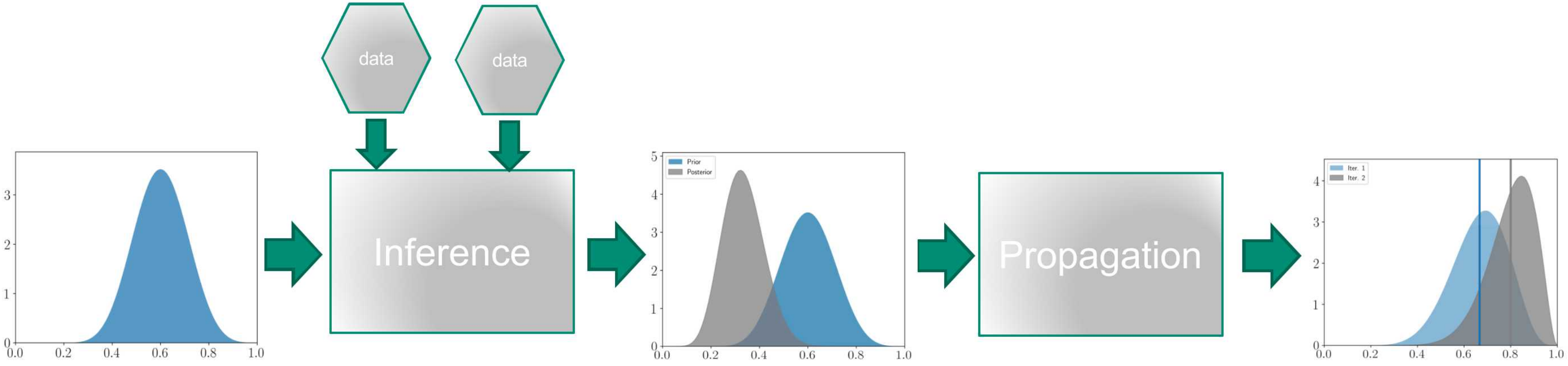


Current UQ Study Overview

Characterization of input uncertainties through assimilation of data
- Prior distributions based on *a priori* knowledge
- Observational data (experiments, reference solutions) → infer posterior distributions
  - Use of data can reduce uncertainty in objective constraints (priors are constrained)
  - Design using prior uncertainties can be overly conservative
  - Reduced uncertainty of data-informed UQ can produce designs with greater performance

Propagation of input uncertainties to response QoI
- Push forward of posterior distributions
- Compute statistics that reflect goals of forward propagation UQ process (i.e., moments, failure probabilities)

Forward Propagation Workflow



(Eldred, M. S.)

Current UQ Study Overview

Current UQ Study Objectives

- Increase number of simulated aleatory uncertain variables; focus on generator power instead of fatigue loads

Dakota-OpenFAST-TurbSim model

- Dakota: Sandia-based UQ and optimization software

List of Analyzed Data Sets

SWiFT Experimental Data

- 973 experimental 10-min bins from wake steering experiment; included bins have active turbines and present data in all needed channels for entire 10-min period

Parametric Simulation Study

- 973 simulated 10-min bins with parametric list inputs set to 10-min bin experimental values (10-min means)

UQ Forward Propagation Study

- 7000 simulated 10-min bins with aleatory uncertain inputs set to 10-min bin experimental values (mean and standard deviation)

Simulated Aleatory Uncertain Variables
Wind Speed
Turbulence Intensity (TI)
Vertical Wind Power law Exponent
Nacelle Yaw Offset
Air Density
Generator Torque Constant

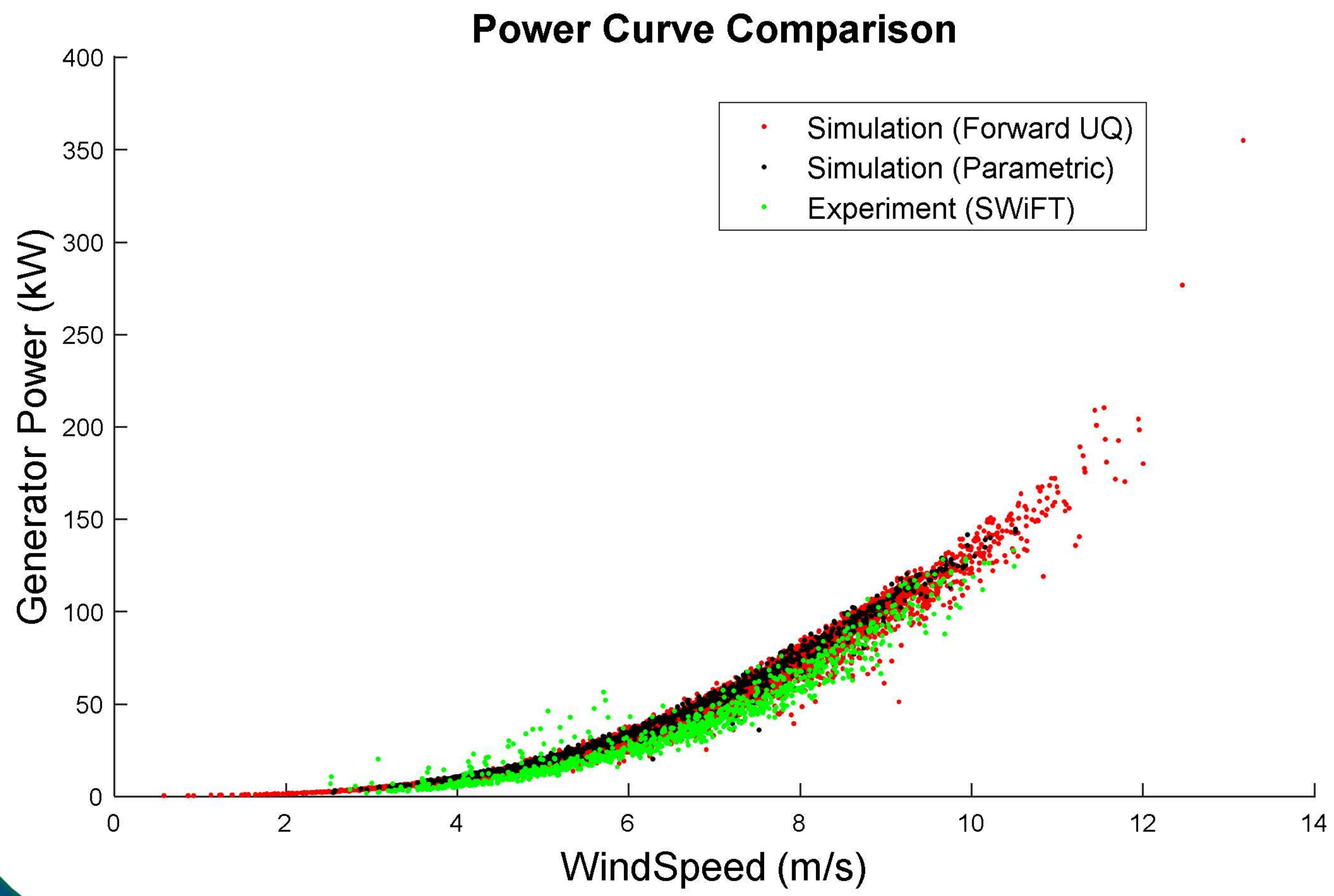
Current UQ Study Results

Results

Power curve comparison between SWiFT experimental results, parametric simulation and forward UQ propagation studies.

- 12-18% global over-prediction for simulated generator power compared to experimental results

- 11-23% global over-prediction of simulated generator power standard deviation compared to experimental results



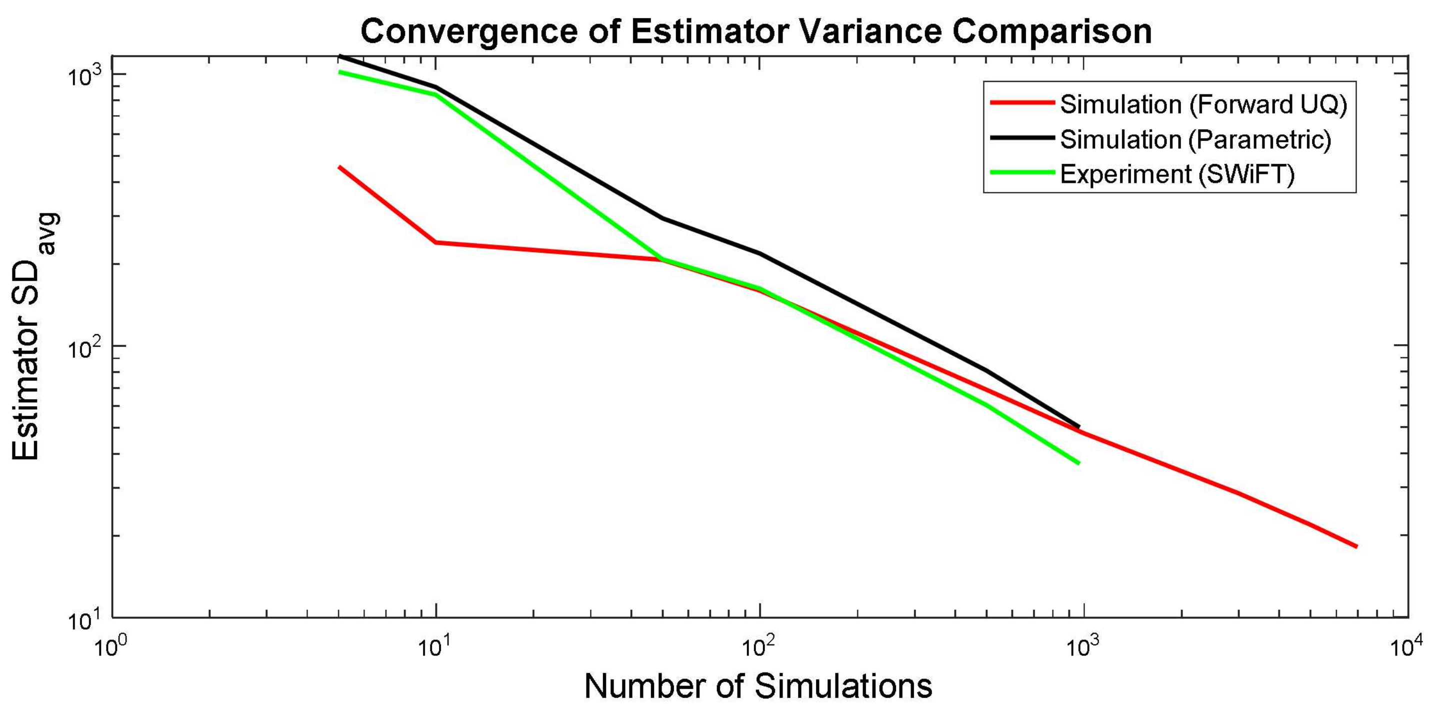
Current UQ Study Results

Results

Estimator variance comparison between SWiFT experimental results, parametric simulation and forward UQ propagation studies for generator power

- Estimator error convergence rate between experiment and parametric simulation rate is within 5%; experiment has lower estimator variance

- Estimator error convergence rate is significantly slower, 37% less than experiment, for the forward UQ simulation study



Future Research Steps

Incorporate other models into MLMF research framework

- WindSE, FAST.Farm, Nalu-Wind (coarse, medium, fine resolution meshes)

Application of other UQ methods beyond forward UQ

Inverse UQ

- Mapping of input parameters to match model outputs. Can be used to inform model changes.

Sensitivity Analysis

- Polynomial chaos expansion (PCE) method determines most sensitive input parameters for model output variance

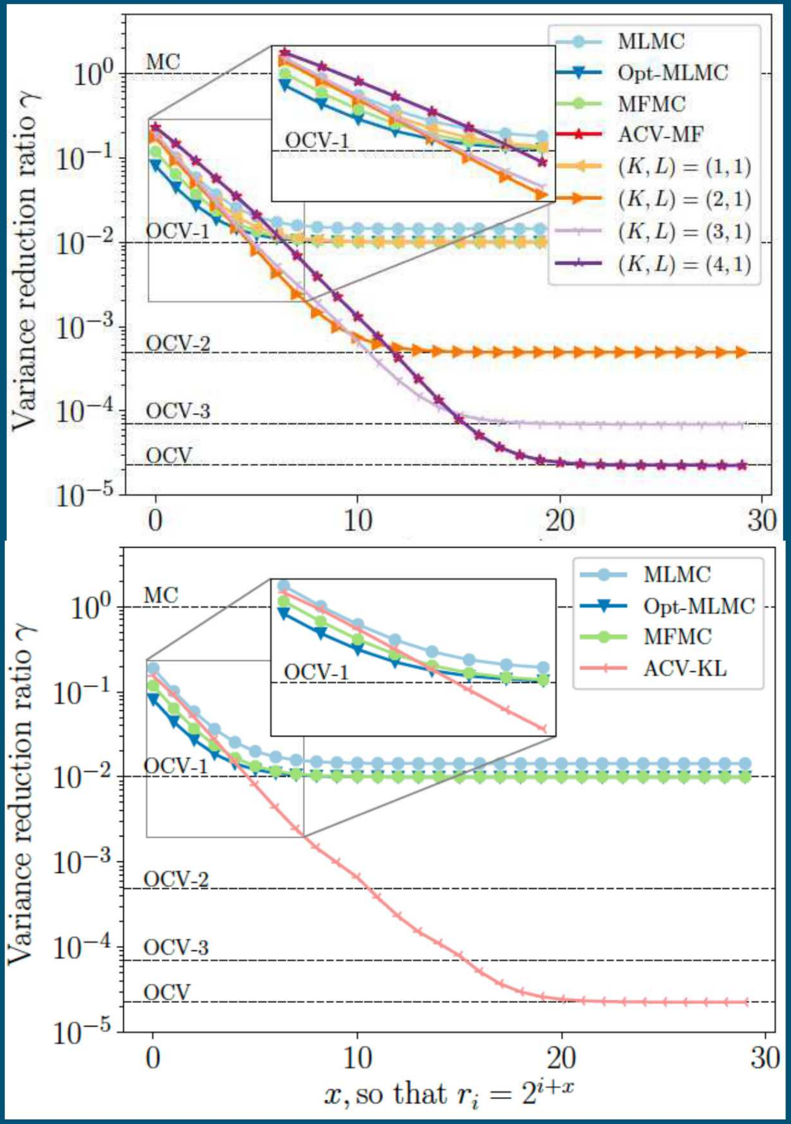
Optimization under Certainty (OUU)

- Optimization problem with adjustments for model and input parameter uncertainties

UQ Research Development

- Compound efficiencies (i.e. enhanced multifidelity control variates)

- Address complexities with component-based approach (i.e. Mixed epistemic-aleatory UQ)



Multilevel-control variate method comparison (Eldred, M. S.)

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