Evaluating Wind Power Prediction Uncertainty Using Scanning Doppler Wind Lidar

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Background: The Power Equation & Manufacturer's Power Curve

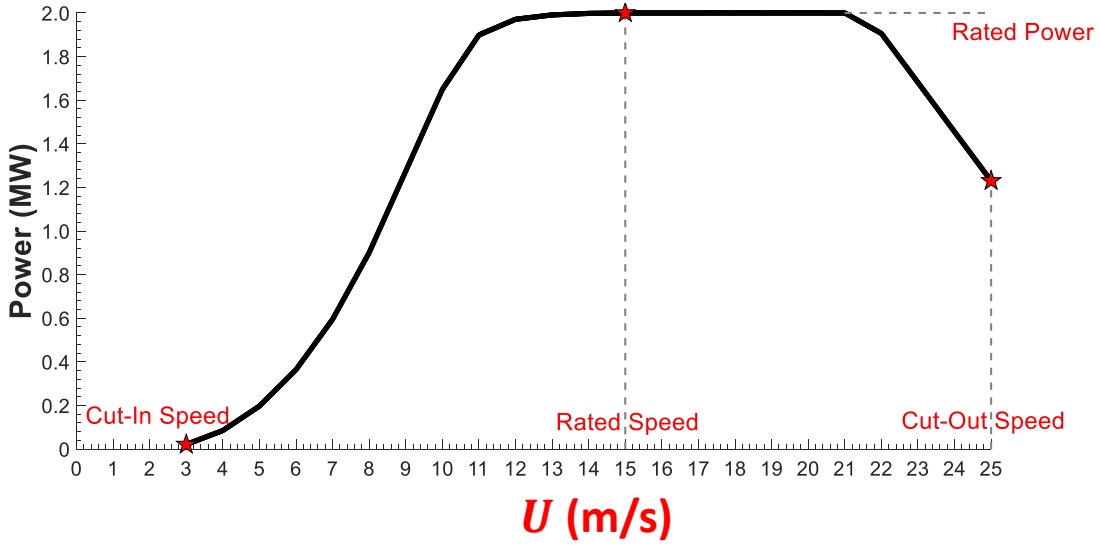
$$\mathbf{Power}_{Estimate} = \underbrace{C_p}_{\text{Efficiency term}} * \underbrace{0.5 * \rho * A * U^3}_{\text{Available Power}}$$

ρ = air density, A = rotor area

C_p = power coefficient - $C_p(U)$

U = wind speed

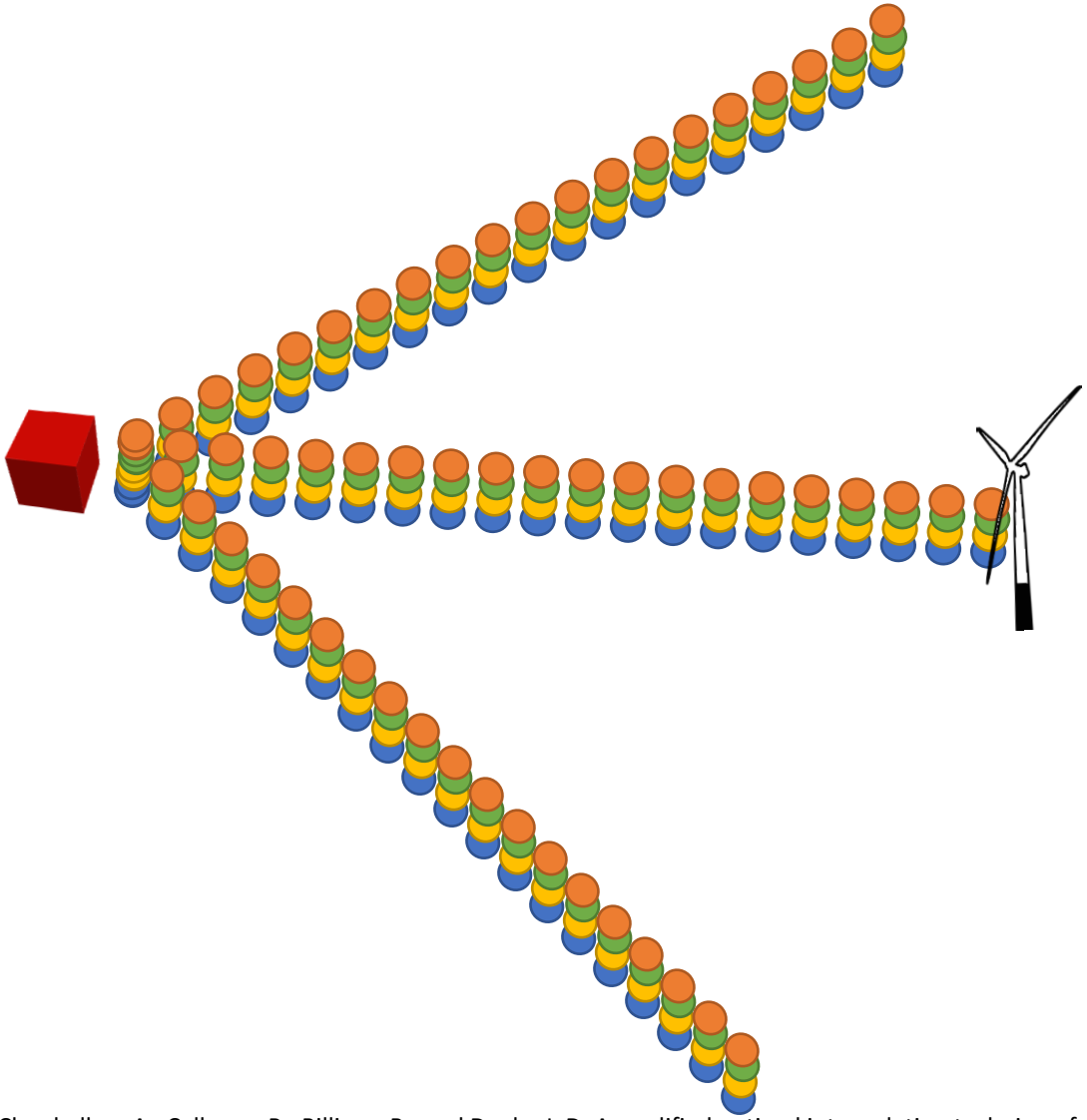
MPC Plots Power as a Function of U



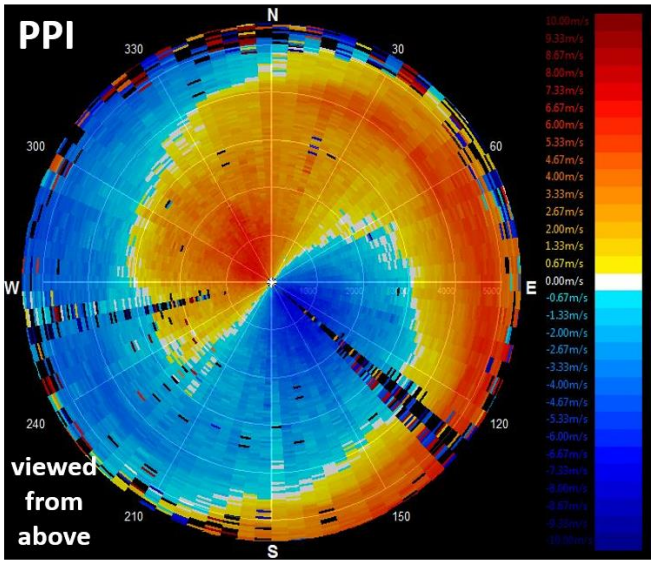
Data Collection: The VERTEX Campaign

- Lewes, Delaware
- September-October 2016
- 2 MW Coastal Turbine (Gamesa)
- Remote Sensing:
  - Wind: Scanning Doppler wind lidar
    - Windcube 200s (~3km)
  - Temperature:
    - Microwave Radiometer

Data Collection: Wind Profile Reconstruction



Plan Position Indicator (PPI) Scans:



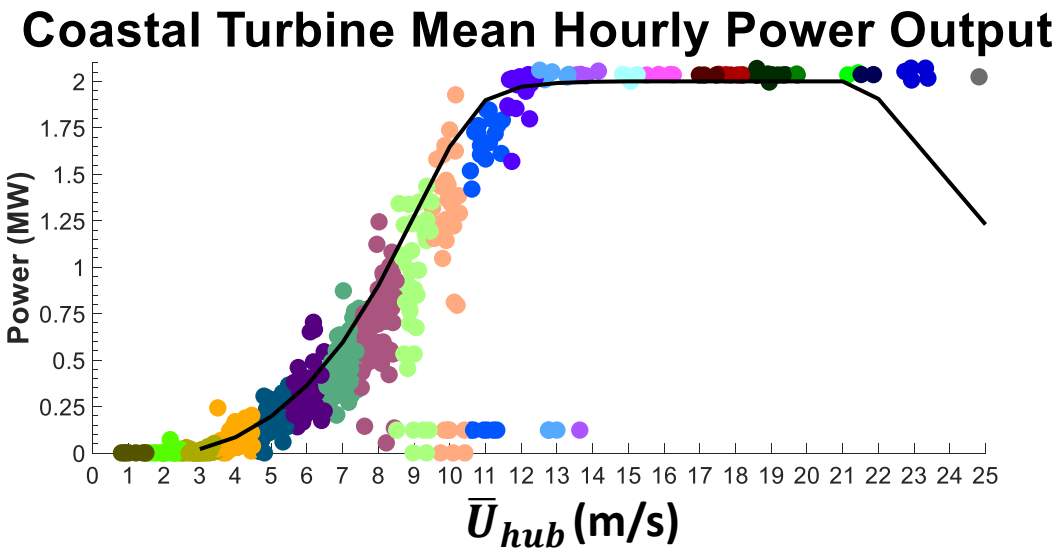
- 200s Lidar
- PPI scan Elevation Angle 1
- PPI scan Elevation Angle 2
- PPI scan Elevation Angle 3
- PPI scan Elevation Angle 4
- OI Reconstructed Profile*

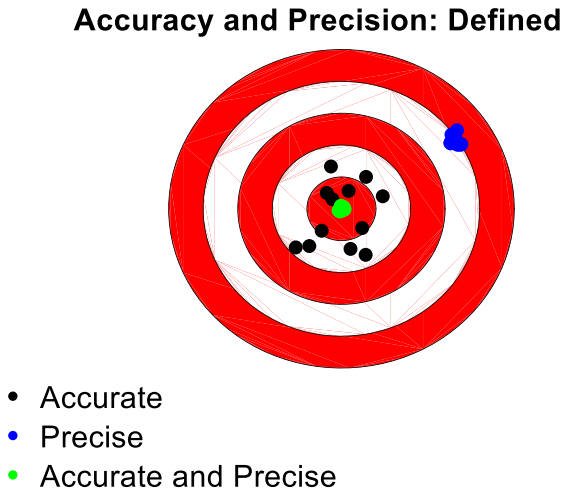
Choukulkar, A., Calhoun, R., Billings, B., and Doyle, J. D. A modified optimal interpolation technique for vector retrieval for coherent doppler lidar. IEEE Geoscience and Remote Sensing Letters, 9(6):1132–1136, 2012.

Motivation: Accurate and Precise Power Curves

OBSERVATION:

Hub-height wind speed alone does not *accurately* and *precisely* predict power

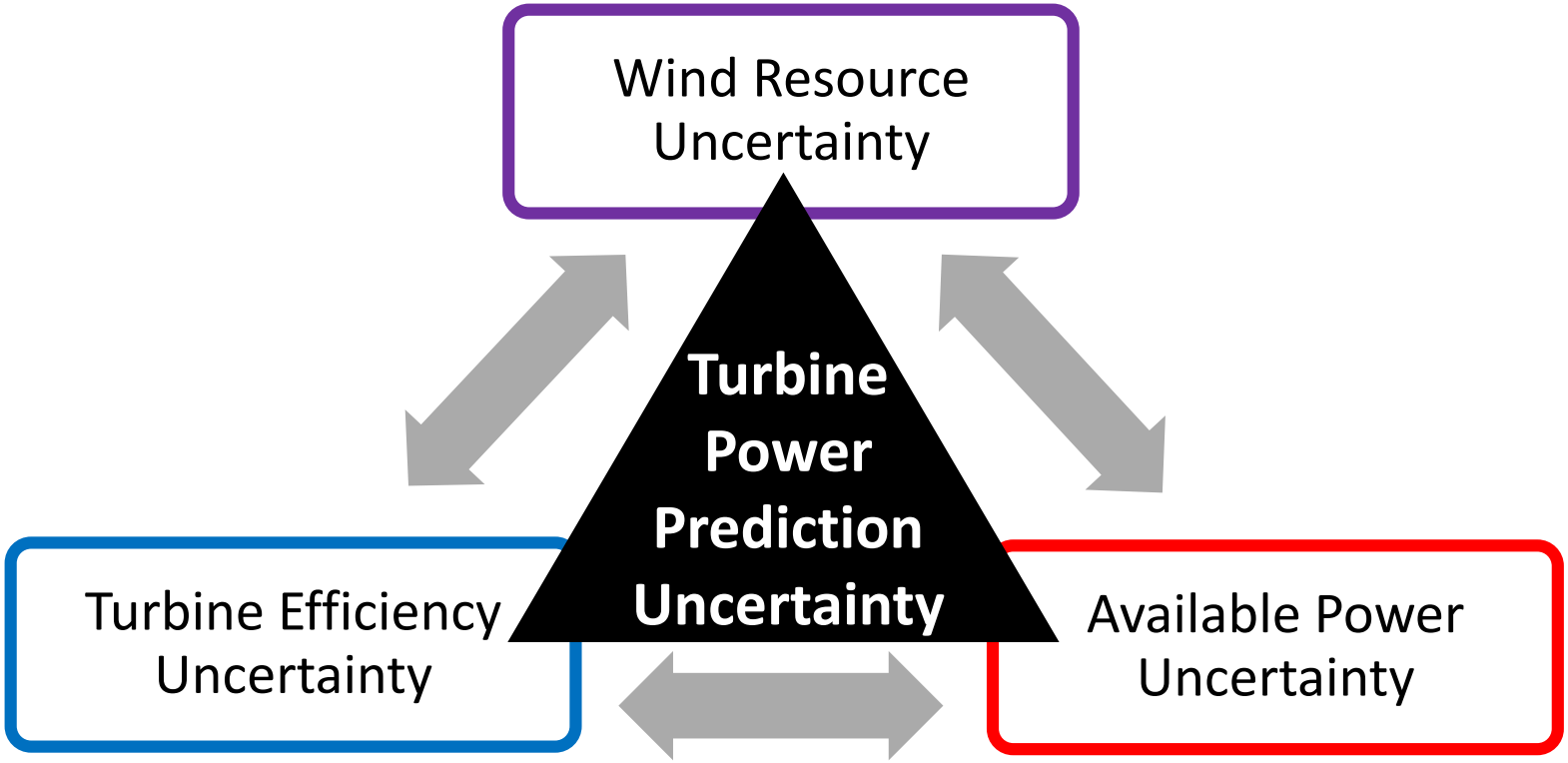




Accuracy – how close output values are to the predicted value

Precision – how close output values are to each other

Method:
The Uncertainty Trifecta

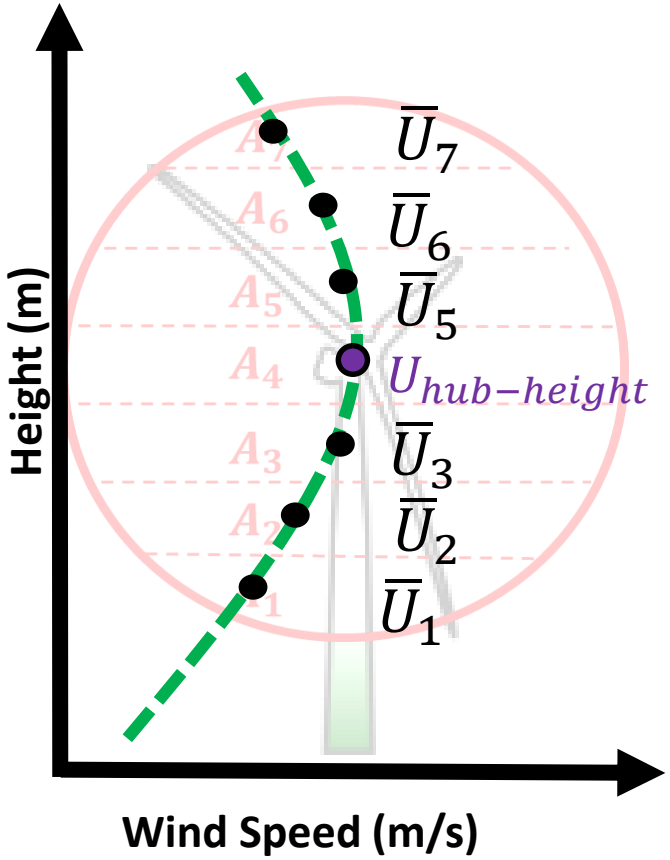


$$\mathbf{Power}_{Estimate} = C_p * 0.5 * \rho * A * U^3$$

Previous Work: Addressing Available Power Uncertainty

$$\text{Power}_{Estimate} = C_p * 0.5 * \rho * A * U^3$$

$$^{\#}U_{REWS} = \sqrt[3]{\frac{1}{A} * \sum_{i=1}^{N} U_i^3 A_i}$$

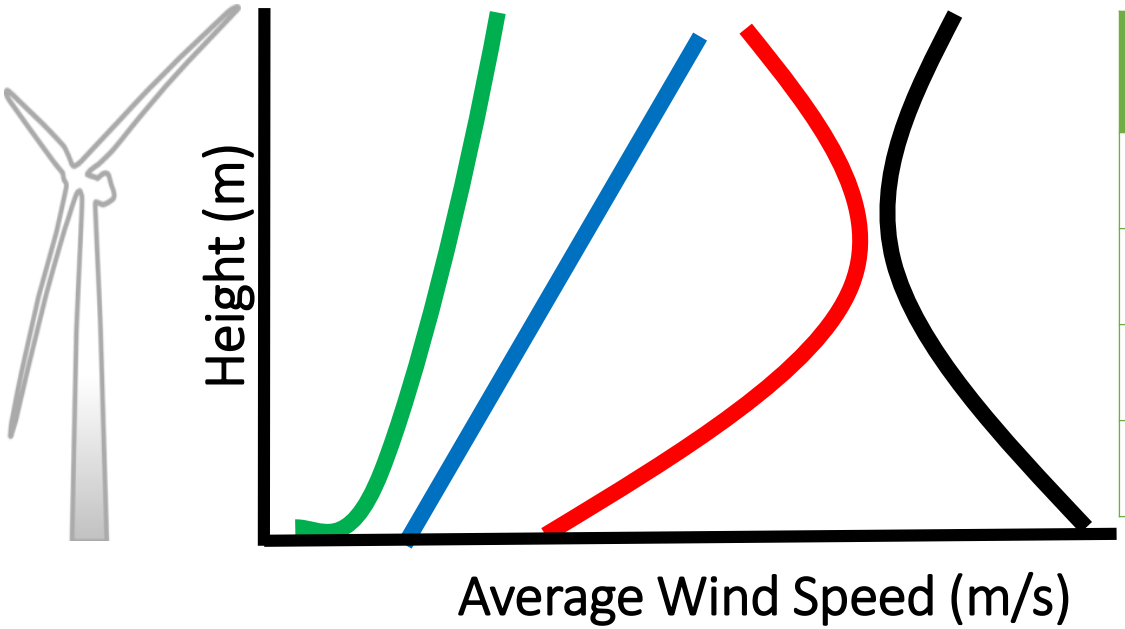


Included IEC standard for available power assessment*

*IEC. Power performance measurements of electricity producing wind turbines edition 2, committee draft 2. Technical Report IEC 61400-12-1, International Electrotechnical Committee; 2017

Wagner R, Antoniou I, Pedersen SM, Courtney MS, Jørgensen HE. The influence of the wind speed profile on wind turbine performance measurements. Wind Energy. 2009;12(4):348-362.

Previous Work: Addressing Wind Resource Uncertainty

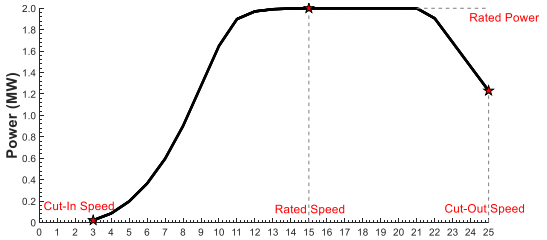


Vertical Wind Profile Types
Power Law
Linear
Strong Inflection
Inverted

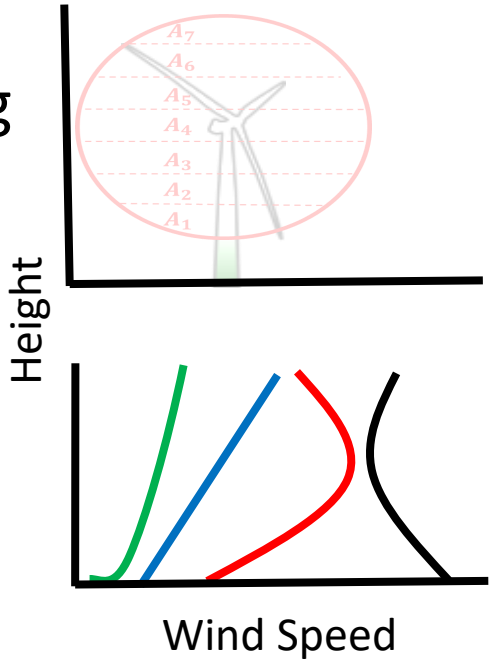
*St Pé A, Sperling M, Brodie JF, Delgado R. Classifying rotor-layer wind to reduce offshore available power uncertainty. Wind Energy. 2018; accepted

Research Questions: Quantifying and Comparing Uncertainty

What is power prediction uncertainty when using hub-height wind speed?

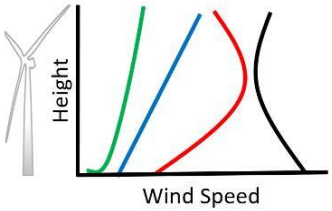


What is the relative power prediction uncertainty reduction achieved by accounting for wind speeds throughout the rotor layer via Wagner REWS?



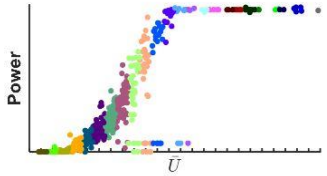
Does the uncertainty of hub-height wind speed and REWS predictions vary during different classified profile types? If so, how?

$$\bar{U} = \bar{U}_{hub}$$

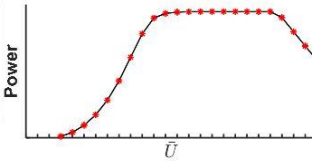


Set model

Bin Speed Terms



Expected Power Curve



Precision Error

$$\boldsymbol{P}_{\boldsymbol{scatter}_j} = \frac{\boldsymbol{\sigma}_j^{\boldsymbol{P}}}{\sqrt{\boldsymbol{N}_j}}$$

Accuracy Error

$$\boldsymbol{P}_{\boldsymbol{bias}_j} = \frac{\mathbf{1}}{\boldsymbol{N}_j}\sum_{\mathbf{i=1}}^{\boldsymbol{N}_j}\left|\boldsymbol{P}_{j_i} - \overline{\boldsymbol{P}_j}\right|$$

FVU

$$FVU = 1 - r^2$$

Compare Predictors

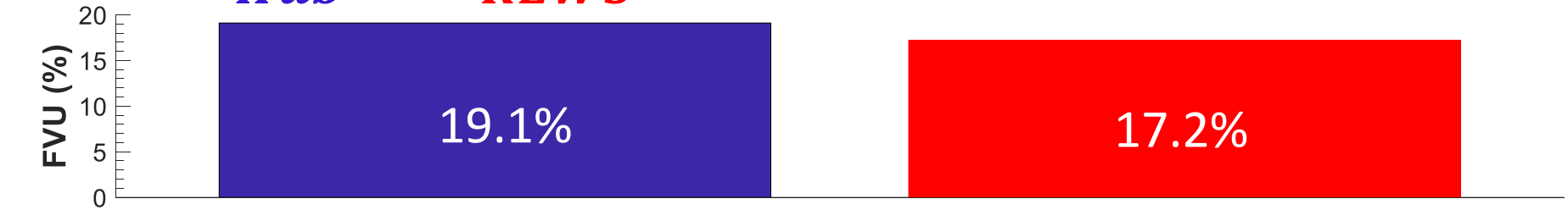
$$\bar{U} = \bar{U}_{REWS}$$

Compare Categories

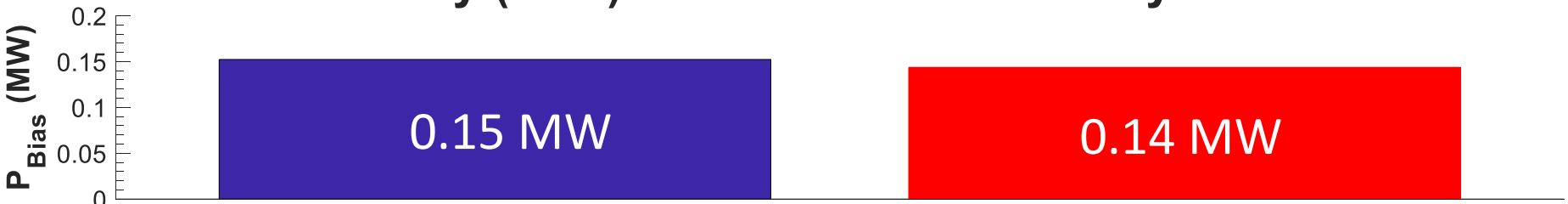
Systematic Evaluation of Power Predictors

Results:
The Value of REWS

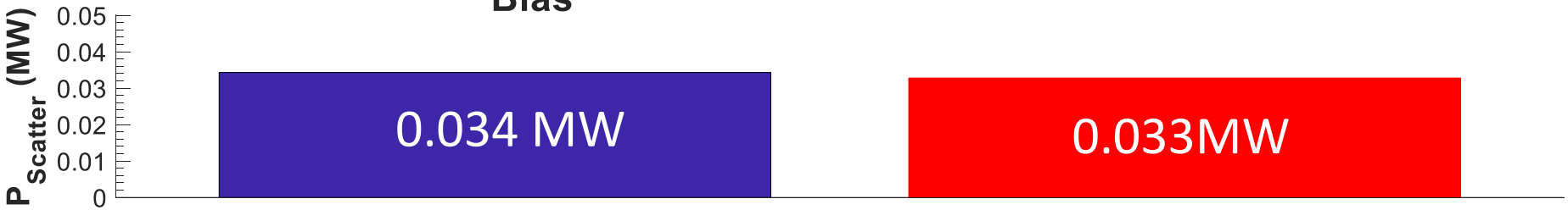
$\overline{U}_{Hub}$ & $\overline{U}_{REWS}$ Prediction Uncertainties



Uncertainty (FVU) Reduction Achieved by REWS: 1.9%



Uncertainty (P_{Bias}) Reduction Achieved by REWS: 0.01MW

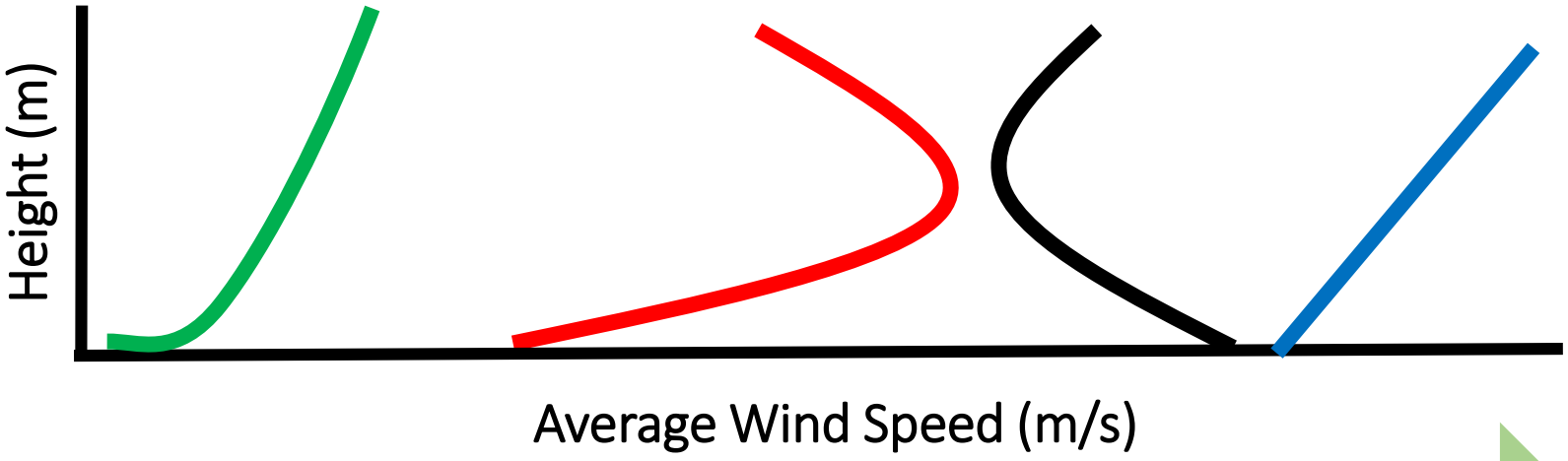


Uncertainty ($P_{Scatter}$) Reduction Achieved by REWS: 0.001MW

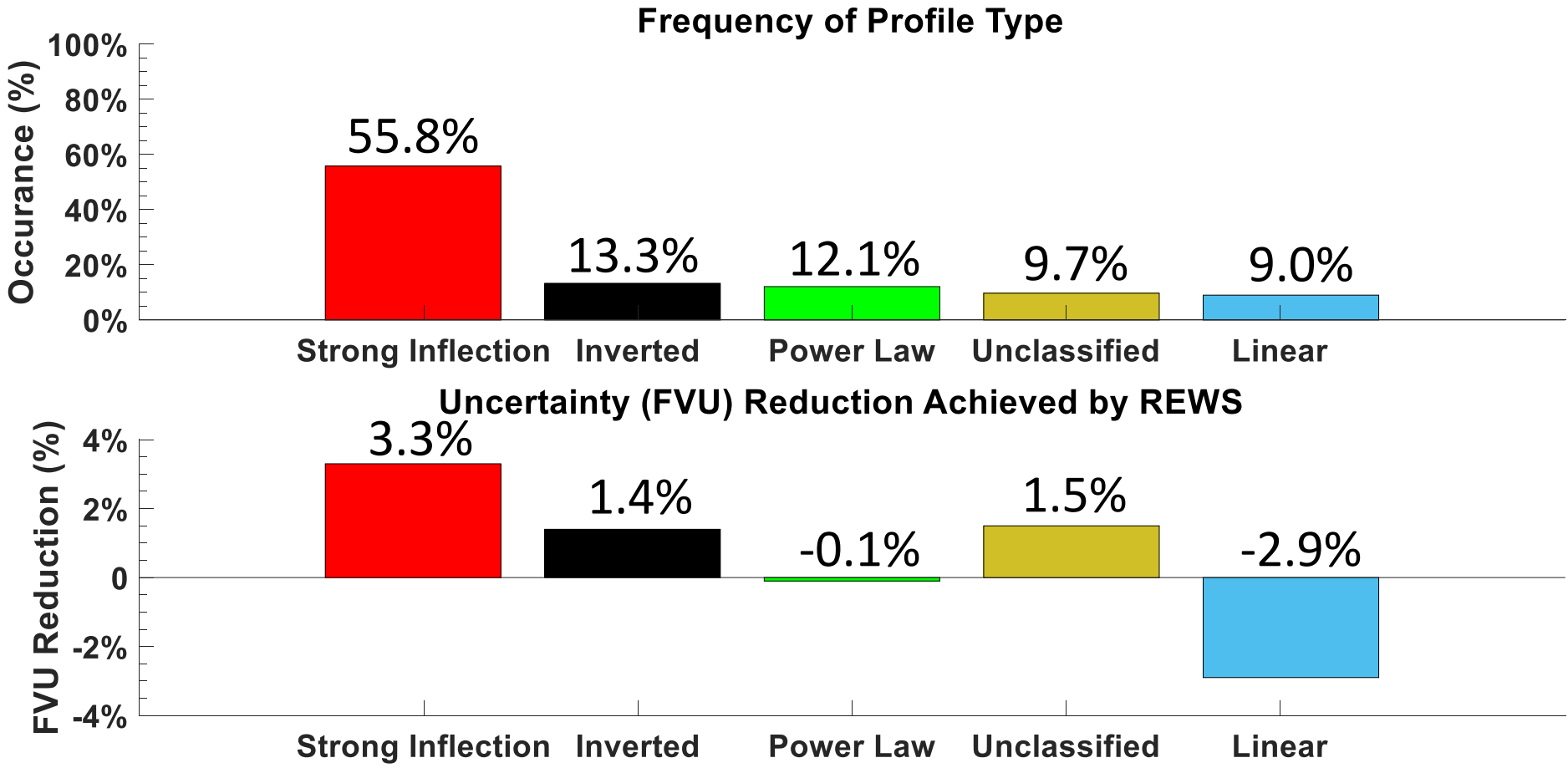
REWS reduces all 3 errors measured

Results: Hub-Height Wind Speed Prediction Uncertainty by Type

Profile Type	Power-Law	Unclassified	Strong Inflections	Inverted	Linear
FVU	7.9%	10.3%	16.3%	31.9%	34.4%
P_{Bias} (MW)	68.6	126.1	143.2	157.1	135.5
$P_{Scatter}$ (MW)	30.8	60.1	45.1	87.8	84.0



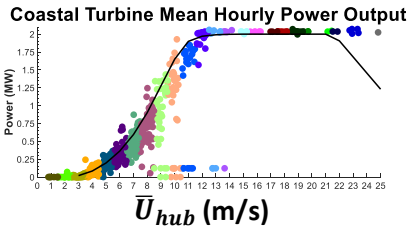
Results:
Relative Value of REWS by Type



Conclusions:

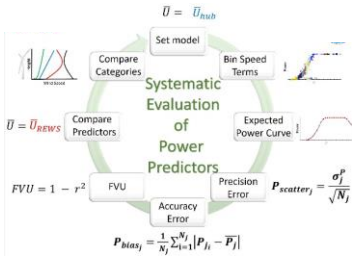
$\bar{U}_{REWS}$ vs. $\bar{U}_{hub}$

- **Overall**, $\bar{U}_{REWS}$ reduces power prediction uncertainty by **1.9%**



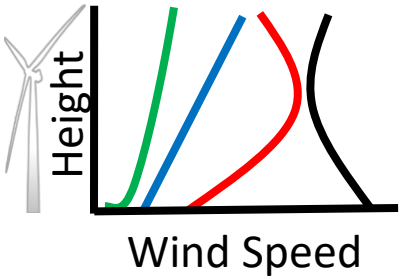
$\bar{U}_{hub}$ uncertainty by classified profile type

- **Standard power-law profiles** have the lowest $\bar{U}_{hub}$ prediction uncertainty (**7.9%**)

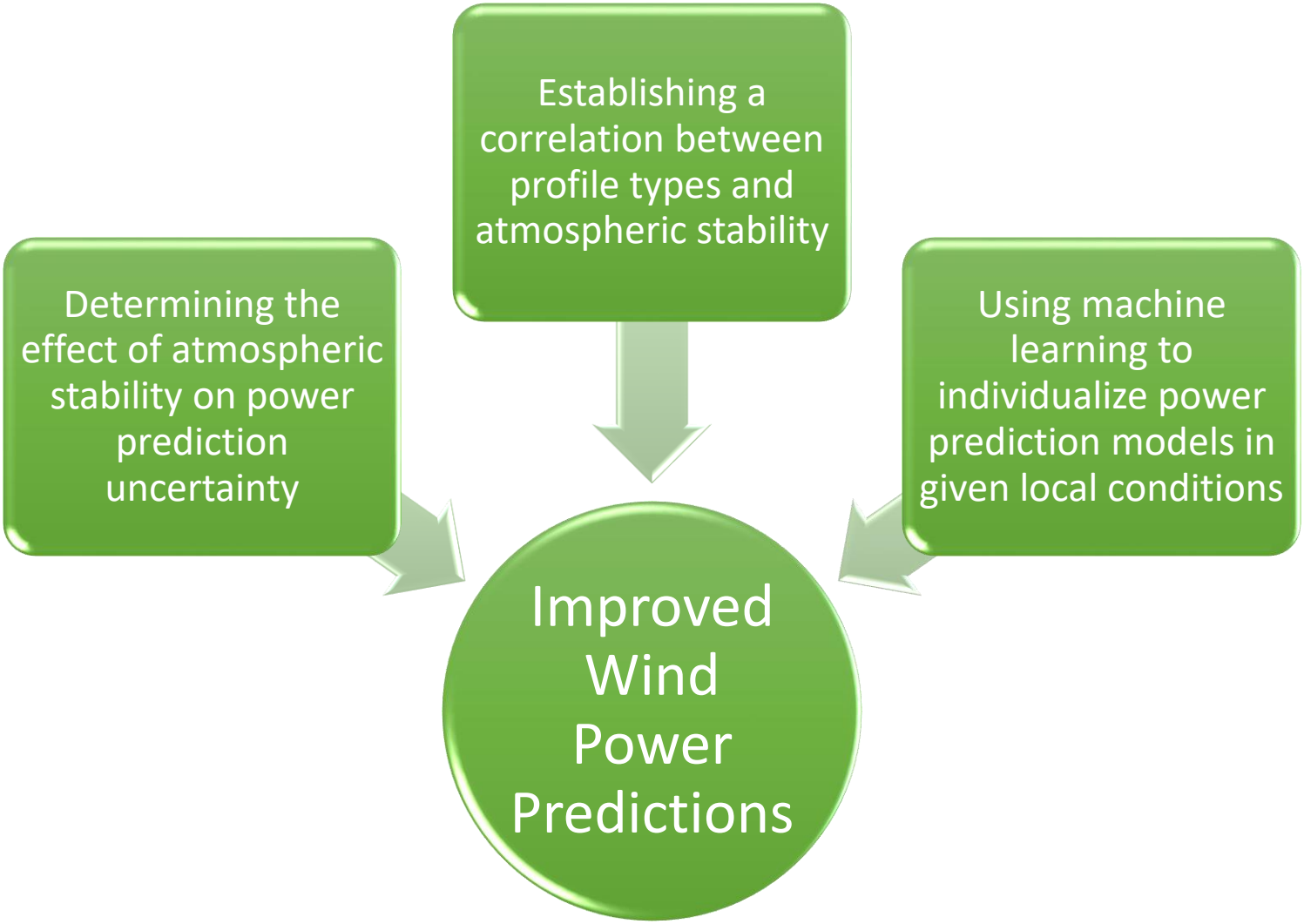


Value of $\bar{U}_{REWS}$ by classified profile type

- **Strong inflection types** have the largest uncertainty reduction achieved by $\bar{U}_{REWS}$ (**3.3%**)



Future Work: Current Research Questions



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Thank you for listening

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