Improving Lidar Turbulence Estimates for Wind Energy

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Can We Replace Meteorological Towers with Lidars?

Meteorological (Met) Towers
- Costly to build
- Not mobile
- Limited by height
- Measure at a point.

Lidars
- Mobile
- Measurements typically extend to 200 meters (m) above ground level
- Measure in a volume.
Sample Lidar Measurements: Atmospheric Radiation Measurement Site

Data from 60 m AGL at Southern Great Plains ARM site
Example of Lidar Versus Sonic Turbulence Intensity

\[ TI = \frac{\sigma_u}{U} \times 100\% \]

Data from Southern Great Plains ARM site
Power curves from FAST simulations of 1.5-MW WindPACT turbine. After Clifton and Wagner (2014).

What Could We Do with Improved Lidar Turbulence Intensity?

- **Research**
  - Study the ABL
  - Characterize inflow
  - Collect wake observations

- **Resource**
  - Replace met towers
  - Classify sites
  - Validate flow models

- **Turbine testing**
  - Test power curves
  - Complete warranty tests
  - Monitor sites

- **Offshore wind**
  - Evaluate design conditions
  - Conduct resource assessments

*Photo by Andrew Clifton, NREL 24383*
The problem: Lidars measure different values of turbulence intensity (TI) than a cup or sonic anemometer. This makes it difficult to use lidars for resource assessment or turbine site suitability.

Proposed solution:
Improve TI estimates using a combination of physics and machine learning in the Lidar Turbulence Error Reduction Algorithm (L-TERRA).
• Testing data sets: Atmospheric Radiation Measurement (ARM) site in Oklahoma and wind power plant in Southern Plains region of United States

• WINDCUBE v2 vertically profiling lidar deployed at both sites near met towers.

Photo by Sonia Wharton
Which Model Chain Minimizes Turbulence Intensity Mean Absolute Error?
ARM Site: Raw

Raw mean absolute error (MAE): 1.5%
ARM Site: After L-TERRA

Raw MAE: 1.5%  L-TERRA MAE: 1.4%

- Stable (N = 1246): \( y = 0.89x \), \( R^2 = 0.88 \)
- Neutral (N = 590): \( y = 0.96x \), \( R^2 = 0.74 \)
- Unstable (N = 1322): \( y = 1.06x \), \( R^2 = 0.78 \)
Wind Power Plant: Raw

Raw MAE: 1.48%

Graph showing the relationship between WindCube TI (%) and Cup TI (%). The graph is divided into four categories:
- Stable (N = 1908): y = 0.92x, R² = 0.89
- Neutral (N = 899): y = 1.10x, R² = 0.86
- Unstable (N = 1885): y = 1.15x, R² = 0.84

The graph indicates a positive correlation between the two variables, with the data points clustering around the linear regression lines for each category.
Wind Power Plant: After L-TERRA

Raw MAE: 1.48%  \[ \text{L-TERRA MAE: 1.39\%} \]

\[
\text{Stable (N = 1866): } y = 0.89x, \ R^2 = 0.92 \\
\text{Neutral (N = 856): } y = 1.02x, \ R^2 = 0.87 \\
\text{Unstable (N = 1771): } y = 1.11x, \ R^2 = 0.84
\]
**Stable:** Small turbulent length scales; volume averaging has large contribution.
Which Model Chain Minimizes Mean Absolute Error for Different Stability Classes?

**Stable:** Small turbulent length scales; volume averaging has large contribution.

**Neutral:** Small effects from both volume averaging and variance contamination.
Which Model Chain Minimizes Mean Absolute Error for Different Stability Classes?

**Stable:** Small turbulent length scales; volume averaging has large contribution.

**Neutral:** Small effects from both volume averaging and variance contamination.

**Unstable:** Strong turbulence; variance contamination has large contribution.

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1. **Start:** Raw WC Data
   - **Pre-Processing:** U, α, T
   - Interpolated time series
   - **Spike Filter**
   - Noise Removal?
     - **Lenschow 1**
     - **Lenschow 2**
     - **Lenschow 3**

2. **Wind Speed?**
   - **Volume Averaging?**
     - Spectral Fit 1
     - Variance Contamination?
       - **Taylor 1**
     - **Spectral Fit 2**
     - **Machine Learning?**
       - Random Forest
       - MARS

3. **Volume Averaging?**
   - Azimuthal Structure Function
   - Variance Contamination?
     - Longitudinal Structure Function
     - Six-Beam Technique

**Terminus:** Start/End
**Output**
**Decision**
ARM Site: Raw

Raw MAE: 1.5%

Stable (N = 1261): $y = 0.90x$. $R^2 = 0.87$
Neutral (N = 627): $y = 1.05x$. $R^2 = 0.89$
Unstable (N = 1480): $y = 1.14x$. $R^2 = 0.81$
ARM Site: After L-TERRA—Stability

- Raw MAE: 1.5%
- L-TERRA MAE: 1.4%
- L-TERRA-S MAE: 1.25%

Graph showing scatter plots for Stable (N = 1246), Neutral (N = 590), and Unstable (N = 1321) conditions, with linear equations and R² values for each category.
Wind Power Plant: Raw

Raw MAE: 1.48%
Wind Power Plant: After L-TERRA—Stability

Raw MAE: 1.48%  L-TERRA MAE: 1.39%  L-TERRA-S MAE: 1.19%

- Stable (N = 1864): $y = 1.00x$. $R^2 = 0.91$
- Neutral (N = 856): $y = 1.02x$. $R^2 = 0.87$
- Unstable (N = 1771): $y = 1.05x$. $R^2 = 0.83$
Sensitivity of Turbulence Intensity Error to Lidar-Measured Parameters

Scanning Circle

Turbulent Motion

Line-of-Sight Velocity

Probe Volume

Emitted Signal

Returned Signal

Lidar
Conducting Sensitivity Analysis

- New IEC 61400-12-1 standards, Annex L: Classification of remote sensing devices

- Sensitivity analysis: Bin input data, and calculate regression line for binned data vs. TI % difference

- **Sensitivity**: Product of slope of regression line and standard deviation of input variable
Sensitivity to Shear

Raw: $y = -102.16x + 19.77. R^2 = 0.96$

L-TERRA-S: $y = -24.23x + 5.96. R^2 = 0.42$
Sensitivity to Turbulence Intensity

Raw: \[ y = 2.47x - 20.33. \quad R^2 = 0.86 \]

L-TERRA-S: \[ y = 0.56x - 4.25. \quad R^2 = 0.31 \]
Sensitivity to Mean Wind Speed

- Raw: $y = -1.44x + 18.28$. $R^2 = 0.44$
- L–TERRA–S: $y = -1.42x + 15.54$. $R^2 = 0.82$
Sensitivity to Signal-to-Noise Ratio

\[
\text{Raw: } y = -2.54x - 27.28. \quad R^2 = 0.82
\]

\[
\text{L-TERRA-S: } y = -2.32x - 26.22. \quad R^2 = 0.74
\]
Variables with Highest Sensitivity

- Int. time (vert.)
- SNR
- Int. time (horiz.)
- U
- Corrected TI
- p
- Original TI
- Int. length (horiz.)
- Stationarity
- Int. length (vert.)
- Roll
- Internal temperature
- u variance
- WS dispersion
- Maximum w
- Vert. WS dispersion
- w variance
- Spectral broadening
- Pitch

Sensitivity (%)
Option 1 to Reduce Turbulence Intensity Error: Machine Learning

• Use most sensitive variables as input parameters for a machine-learning model.

• Train model with wind power plant data, and test on ARM site data.
ARM Site: After L-TERRA-S

L-TERRA-S MAE: 1.25%
ARM Site: After L-TERRA-S + Machine Learning

L-TERRA-S MAE: 1.25%  L-TERRA-S + ML MAE: 1.29%

Bias due to differing sensitivities between the two sites
Option 2: Examining Error Sources with Virtual Lidar

- Use large-eddy simulation data from NREL’s Simulator for On/Offshore Wind Farm Applications (SOWFA).
- Sample with virtual lidar.

For more information, see https://nwtc.nrel.gov/SOWFA.
Final Thoughts

• L-TERRA reduces lidar TI error under most conditions.

• Current work focuses on understanding all the physics that affect lidar TI error.

• Results highlight the importance of developing dynamic TI corrections that depend on current flow conditions.

Image from Andrew Clifton, NREL
Let’s talk!

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Photo by Sonia Wharton

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