Machine learning improvements to WindCube turbulence intensity measurements at five sites in Northern Europe

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Motivation

- Lidar turbulence intensity (TI) measurements generally show ~10% high biases compared to cup anemometers, and lower R2 than for wind speed.
- In wind energy development, Site Suitability analysis today requires cup anemometer TI measurements to estimate the fatigue loads on the turbines.
- Lidar TI measurements are not generally accepted for this analysis today.
- If we can correct lidar TI measurements and demonstrate good agreement with cup TI, this will allow for complete wind energy development with “standalone” lidar: both Energy Yield Assessment (EYA) and Site Suitability analysis.
- Industry groups such as CFARS and the DNV-JIP are hard at work on this topic.
Approach

To test whether a pure machine learning approach can adjust WindCube TI adequately for use with Site Suitability, you need a sufficient dataset.

**What makes a dataset sufficient?**

1. Training and testing data must be drawn from similar distributions.
2. Training data must cover as wide a range of conditions as is to be expected in model’s application to future data.

Planetary boundary layer wind turbulence, in flat terrain, measured by Class 1 anemometry on IEC-complaint met masts and by collocated, identical wind lidars, with sufficient seasonality to include representative ranges of atmospheric parameters such as wind speed, wind shear, temperature, and stability.
**Dataset**

Timeline of Data, WindCube TI Project

- 14 WindCube lidars
- 4 flat terrain sites in Northern Europe (1 screened out)
- Class 1 anemometry
- IEC-compliant towers
- Good seasonal distribution
- All devices WindCube v2.1
- Line-of-sight (LOS) 1Hz data reprocessed with scalar, vector, hybrid wind field reconstruction
- Additional LOS statistics generated for all five beam directions
- 221K samples, ~5.5 years of data
The XGBoost model is:

- **Supervised**: the features are trained using an objective function (RMSE in our case) to the mast TI (“labels” or “targets”).
- **Ensemble**: hundreds of weak learners are combined to make the prediction.
- **Bootstrap aggregated (“bagged”)**: only a random subset of the data is used to train each weak learner.
- **Gradient-boosted**: each tree is trained sequentially, with the poorest performing predictions given higher weighting (boosted) in each new, weak learner. The weights are determined by the (gradient) of the loss function.
- **Classification and Regression Tree (CART)**: each weak learner in the ensemble is a decision tree.
Feature + label engineering

Features
- Vector, Scalar, and Hybrid WFR wind speeds
- Vector, Scalar, Hybrid WFR turbulence intensity
- Normalized vertical LOS standard deviation ($\theta_\infty$)
- Other LOS statistical data
- Standard deviation of wind direction
- Wind shear, wind veer

Labels
- TI Error, Percent
- TI Error, Difference
- Standard Deviation Error, Percent
- Standard Deviation Error, Difference
- Mast Standard Deviation

Cross validation

Leave one site out
- All results presented are from cross validation
- Each site weighted equally in training
- 75%/25% split for each test site

Leave One Site Out

Train
- [Bar chart showing train data]

Test
- [Bar chart showing test data]
# Various KPI results

<table>
<thead>
<tr>
<th>Linear regression</th>
<th>Slope</th>
<th>Intercept</th>
<th>Bias</th>
<th>R2</th>
</tr>
</thead>
<tbody>
<tr>
<td>WindCube MLTI</td>
<td>0.988</td>
<td>0.003</td>
<td>1.007</td>
<td>0.901</td>
</tr>
<tr>
<td>WindCube v2.1</td>
<td>0.854</td>
<td>0.010</td>
<td>0.928</td>
<td>0.884</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Wind speed binned Tl</th>
<th>Average: relative mean bias error</th>
<th>RMS: relative mean bias error</th>
<th>% within ±5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>WindCube MLTI</td>
<td>-0.5%</td>
<td>3.2%</td>
<td>89.0%</td>
</tr>
<tr>
<td>WindCube v2.1</td>
<td>7.0%</td>
<td>8.7%</td>
<td>35.8%</td>
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<td>33.8%</td>
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</tbody>
</table>
Wind speed binned relative mean bias error
Average TI relative mean bias error by average mast TI

WindCube v2.1: Mast TI vs. Average TI Relative Bias

WindCube MLTI: Mast TI vs. Average TI Relative Bias

Site

1

2

3

4

Restricted
Average TI relative mean bias error by average mast TI

- Proof of concept successful:
  - Machine learning can be used to greatly improve lidar TI
- All KPIs show substantial improvement:
  - Regression slopes and $R^2$, average TI error, wind speed bin mean TI error
- What are the limits of this model's applicability?
  - Sites are on the lower end of global TI distributions How does it perform in the American Midwest?
- Apply machine learning to different site distributions:
  - Complex terrain, offshore, forested, high TI, cold climate, et al
- Ongoing industry collaborations CFARS and DNV-JIP to further validate model
  - Test + improve model according Turbine OEM, IE, and developer consensus KPIs
Thank you

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