Power and load prediction using lidar measurements and deep learning

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Acknowledgements: Funding EUDP grant 64019-0580 for the LIdar-assisted COntrol for REliability IMprovement (LICOREIM) project (Jan. 2020- Dec. 2022).
Content

• Motivation
• Experimental setup
• Data description and processing
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Motivation

- Increase AEP through an improved representation of real-time wind inflow
- Reduction of structural loads – both fatigue and extreme using feed-forward control strategies
- Wind class upgrade of wind turbines to operate at sites with a more severe wind climate than original intended
- Optimal power production in cases of specific load and grid requirement using dynamic power rating from real-time turbulence intensity
Experimental setup

• Test turbine
  – Vestas V52 (850 kW)
  – 50 Hz strain gauge system

• Lidar systems
  – Nacelle-mounted CW lidar
  – 2- and 4-beamed system

• Meteorological mast
Time series example

- Target features are electrical power and blade flapwise bending moment

- Input features are lidar signals are given as LOS wind speeds which can be transformed into wind speed components
Pre-processing

- Initial filtering on 10-min statistics

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Condition</th>
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<tr>
<td>Wind speed [m/s]</td>
<td>$4 &lt; U$</td>
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<tr>
<td>Wind direction [deg]</td>
<td>$265 &lt; \theta &lt; 295$</td>
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<tr>
<td>El. power [kW]</td>
<td>$0 &lt; P$</td>
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<td>Rotational speed [RPM]</td>
<td>$16 &lt; \Omega$</td>
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<td>Collective pitch [deg]</td>
<td>$\theta_p &lt; 23$</td>
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- Caption matrix showing distribution of wind speed and TI
Time delay analysis

Flapwise bending

Power

|\[ \Re_{\delta_{\tau}}(\tau) \]|
|---|---|---|
| 0 | 5 | 10 | 15 | 20 | 25 | 30 | 35 | 40 |
| 0.76 | 0.78 | 0.80 | 0.82 | 0.84 | 0.86 | 0.88 | 0.90 | 0.92 |

2-beamed  4-beamed  met mast

|\[ \Re_{\delta_{\tau}}(\tau) \]|
Time delay analysis

![Graphs showing time delay analysis results for Met mast, 2-beamed, and 4-beamed configurations.](image)

- **Met mast**: Theoretical vs. observed U [m/s] vs. \(\tau\) [s] for the theoretical and observed data points.
- **2-beamed**: Similar graph as Met mast, showing theoretical and observed data.
- **4-beamed**: Graph showing theoretical and observed data, with a different x-axis range compared to the others.
Sequence-to-sequence modelling

- Sequential transformation of input/outputs
  - Specifying \( n_{\text{lag}} \) and \( n_{\text{out}} \)
- Padding and masking
- Structure into tensor format

![Diagram of sequence-to-sequence modelling]

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Recurrent neural networks

- Uses hidden states to process sequences and allows information to persist
- Common types are:
  - GRU
  - LSTM

- Network architecture:
  - Two layers with 50 units in each layer
Forecast horizon performance

Power

- MAE [kW]
- time ahead [s]
- persistence
- 2-beam GRU
- 4-beam GRU
- 2-beam LSTM
- 4-beam LSTM

Flapwise bending moment

- MAE [kN\text{m}]
- time ahead [s]
Multi-step power forecast

2-beamed LSTM model

\[ y = 0.96x + 17.54 \]
\[ R^2 = 0.9557 \]
\[ MAE = 22.55 \]
\[ n = 63945 \]

4-beamed LSTM model

\[ y = 0.99x + 6.00 \]
\[ R^2 = 0.9922 \]
\[ MAE = 21.06 \]
\[ n = 113295 \]
Multi-step flapwise bending moment forecast

2-beamed LSTM model

4-beamed LSTM model
Limitations

- Model is trained on low-turbulent data only
- Underestimation due to down-sampling of power and load signals
- Time to impact varies with wind speed
- Rotor-plane is generalized based on finite number of measuring points
Questions