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).

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Motivation

- Increase AEP through an improved representation of real-time wind inflow

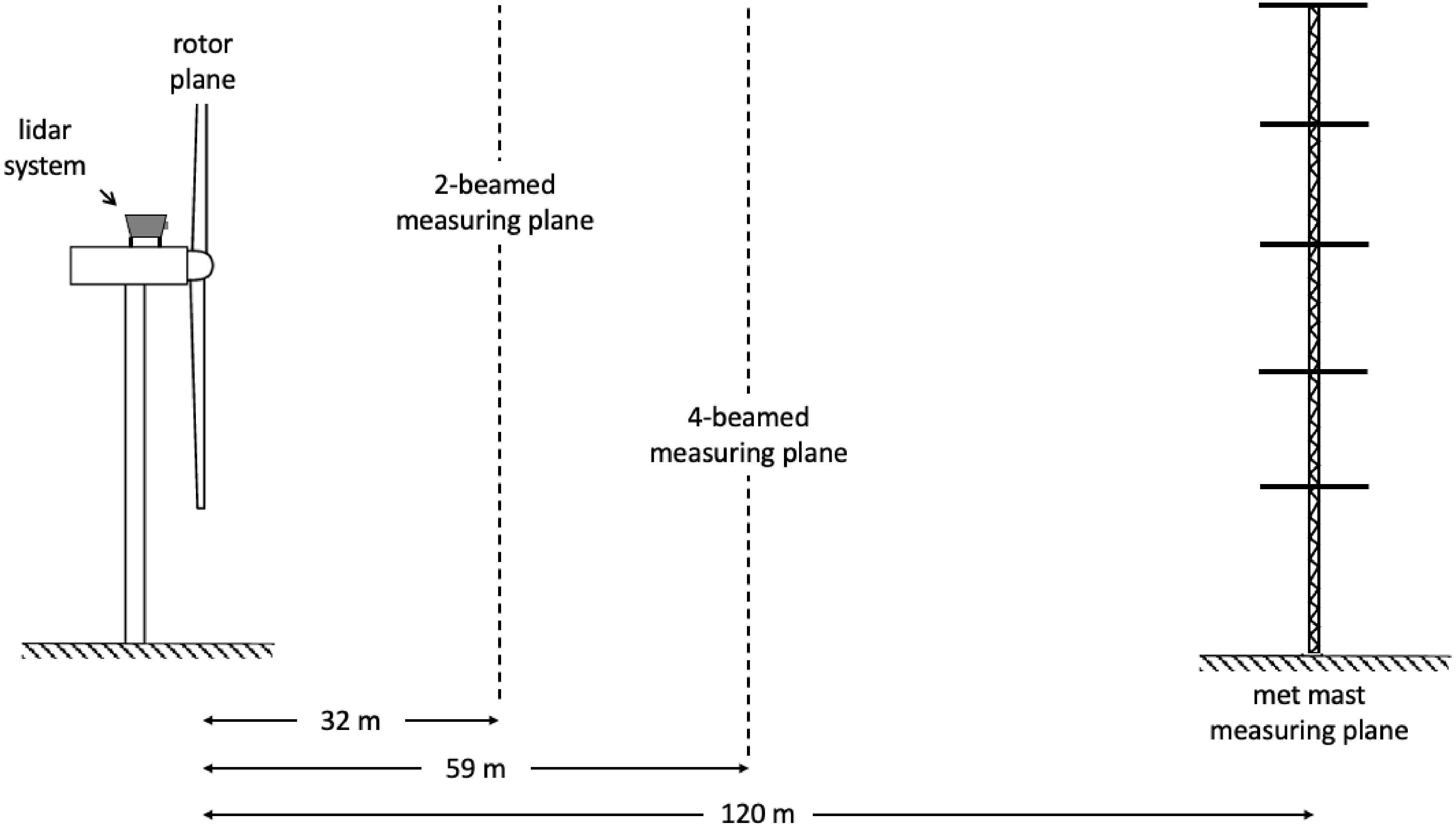
- Reduction of structural loads – both fatigue and extreme using feed-forward control strategies

- Wind class upgrade of wind turbines to operate at sites with a more severe wind climate than original intended

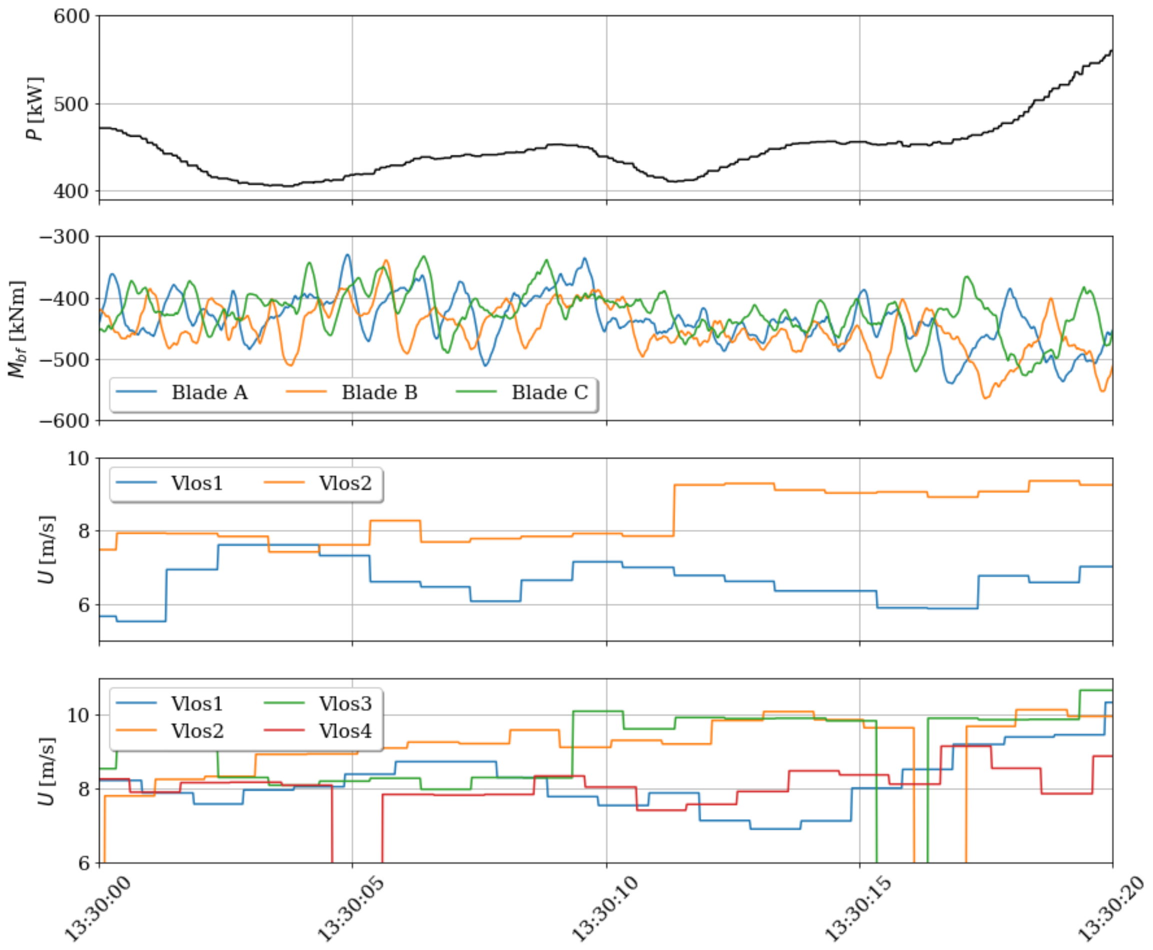
- Optimal power production in cases of specific load and grid requirement using dynamic power rating from real-time turbulence intensity

Experimental setup

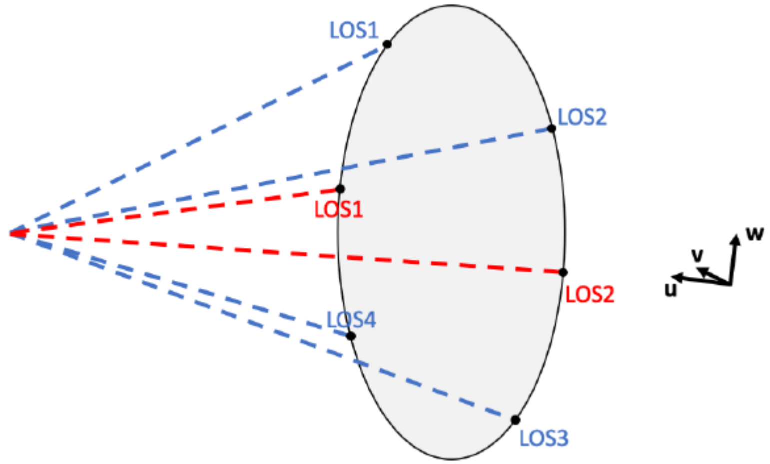
- Test turbine
  - Vestas V52 (850 kW)
  - 50 Hz strain gauge system
- Lidar systems
  - Nacelle-mounted CW lidar
  - 2- and 4-beamed system
- Meteorological mast



Time series example



- Target features are electrical power and blade flapwise bending moment
- Input features are lidar signals are gives as LOS wind speeds which can be transformed into wind speed components

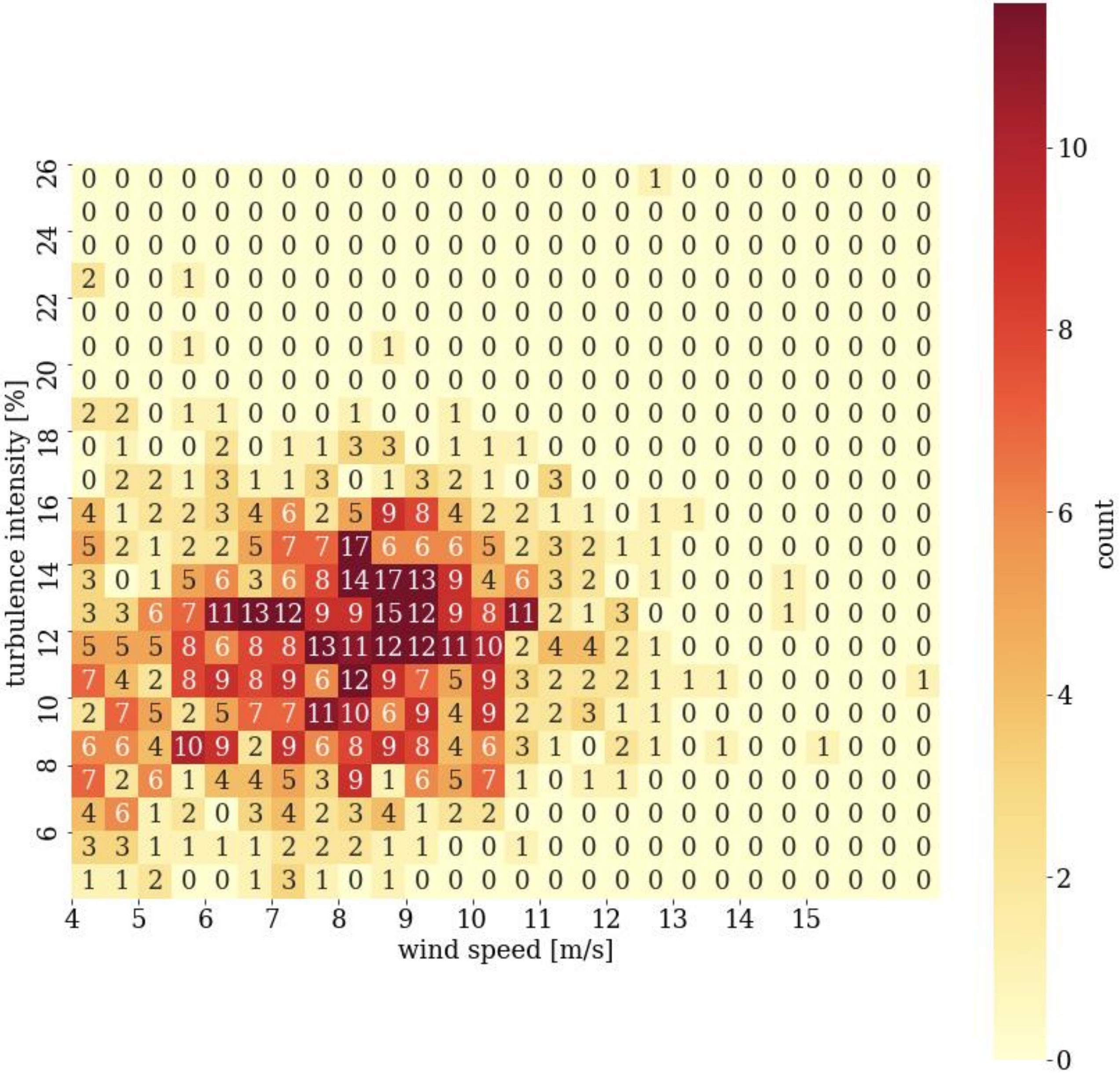


Pre-processing

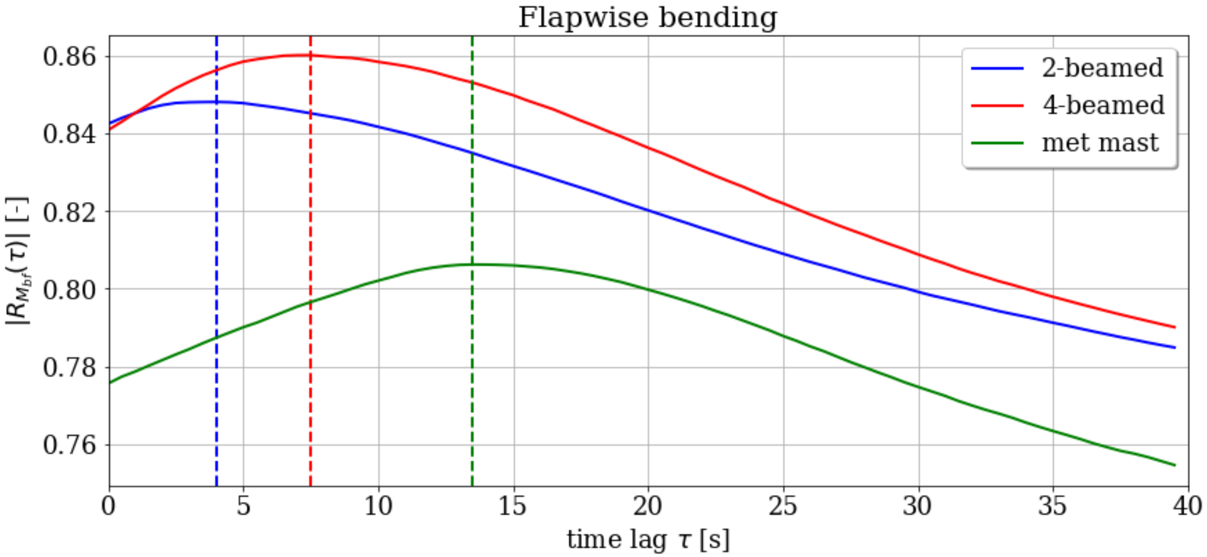
- Initial filtering on 10-min statistics

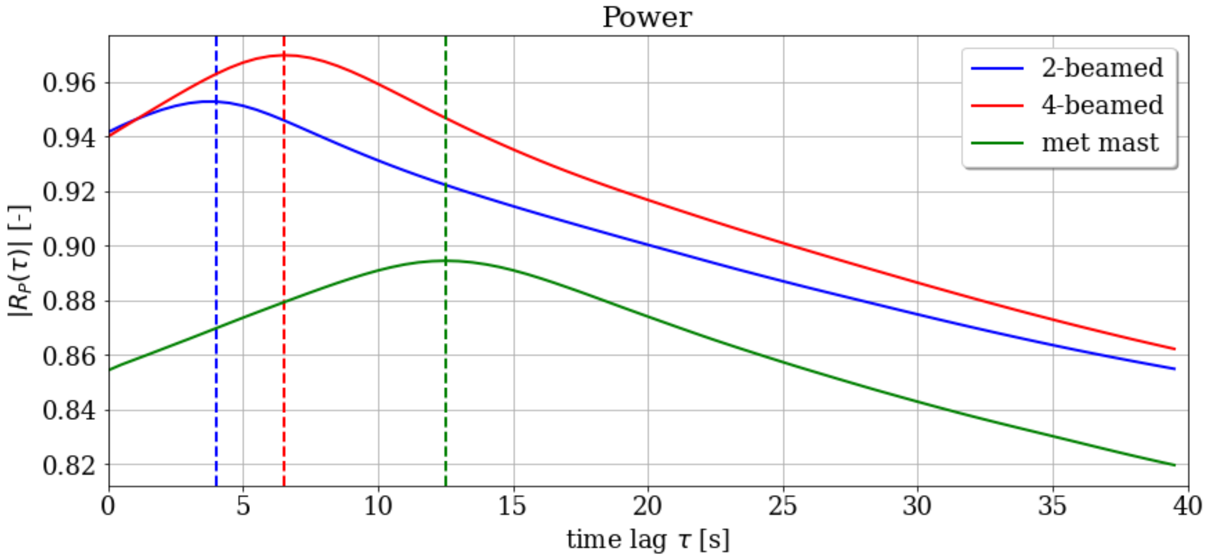
Parameter		Condition
Wind speed	[m/s]	$4 < U$
Wind direction	[deg]	$265 < \theta < 295$
El. power	[kW]	$0 < P$
Rotational speed	[RPM]	$16 < \Omega$
Collective pitch	[deg]	$\theta_p < 23$

- Caption matrix showing distribution of wind speed and TI

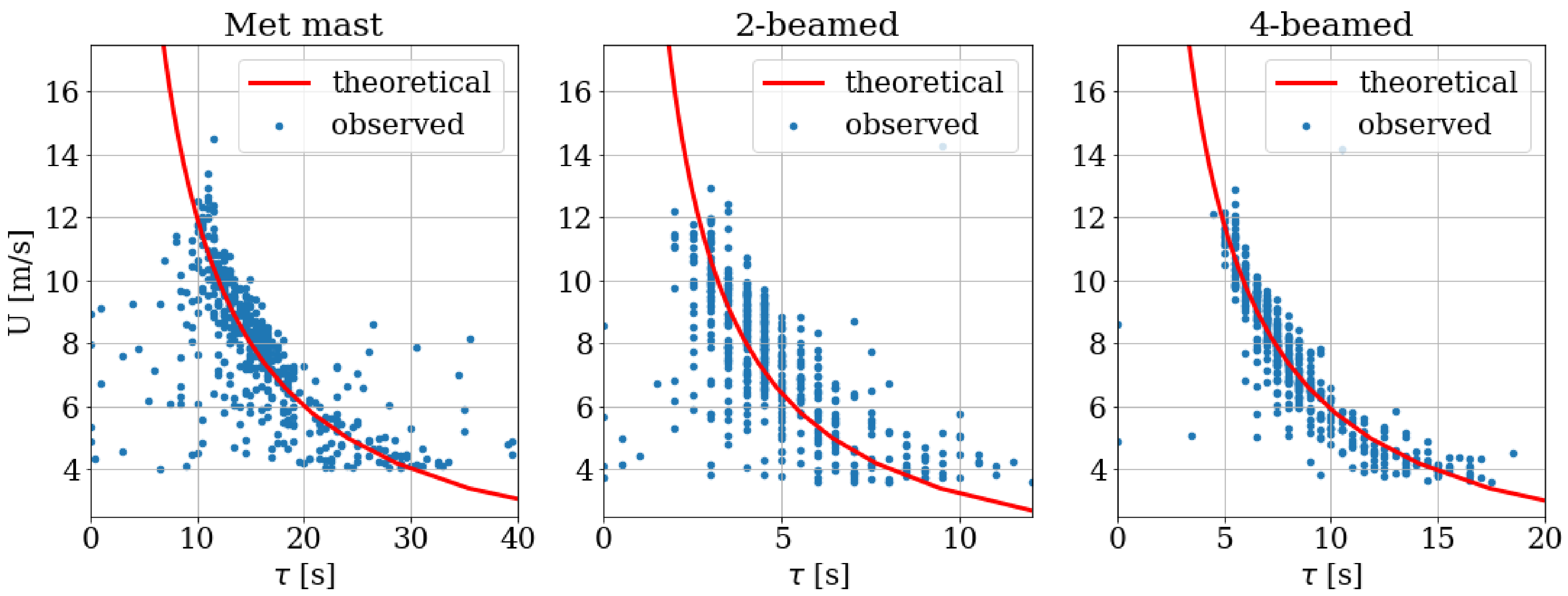


Time delay analysis



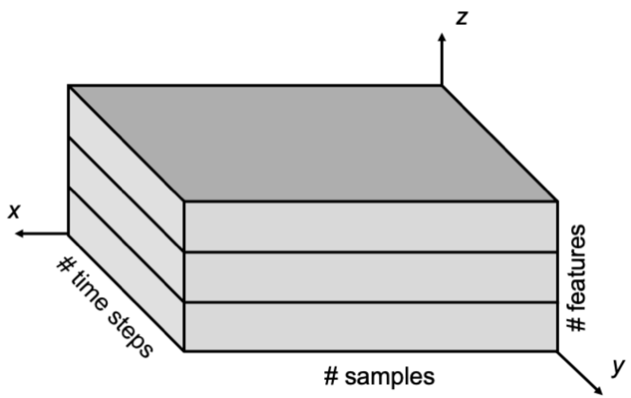


Time delay analysis



Sequence-to-sequence modelling

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



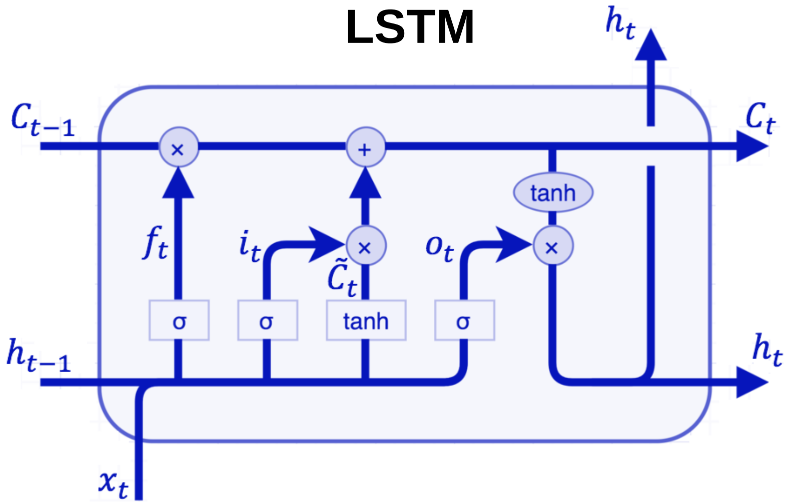
t	x_1^{t-1}	x_2^{t-1}	x_1^{t-2}	x_2^{t-2}	x_1^{t-3}	x_2^{t-3}	y_1^t	y_1^{t+1}	y_1^{t+2}
2020-08-01 12:30:00	NaN	NaN	NaN	NaN	NaN	NaN	189.62	173.60	168.57
2020-08-01 12:30:01	6.34	5.25	NaN	NaN	NaN	NaN	173.60	168.57	181.02
2020-08-01 12:30:02	5.92	4.42	6.34	5.25	NaN	NaN	168.57	181.02	...
2020-08-01 12:30:03	3.37	4.36	5.92	4.42	6.34	5.25	181.02	...	...
...	...	...	...	...	...	...	...	...	...
2020-08-01 12:39:56	7.45	6.89	...	...	...	...	268.31	245.89	263.66
2020-08-01 12:39:57	8.01	7.11	7.45	6.89	...	...	245.89	263.66	257.12
2020-08-01 12:39:58	7.78	6.34	8.01	7.11	7.45	6.89	263.66	257.12	NaN
2020-08-01 12:39:59	9.29	5.73	7.78	6.34	8.01	7.11	257.12	NaN	NaN

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

LSTM

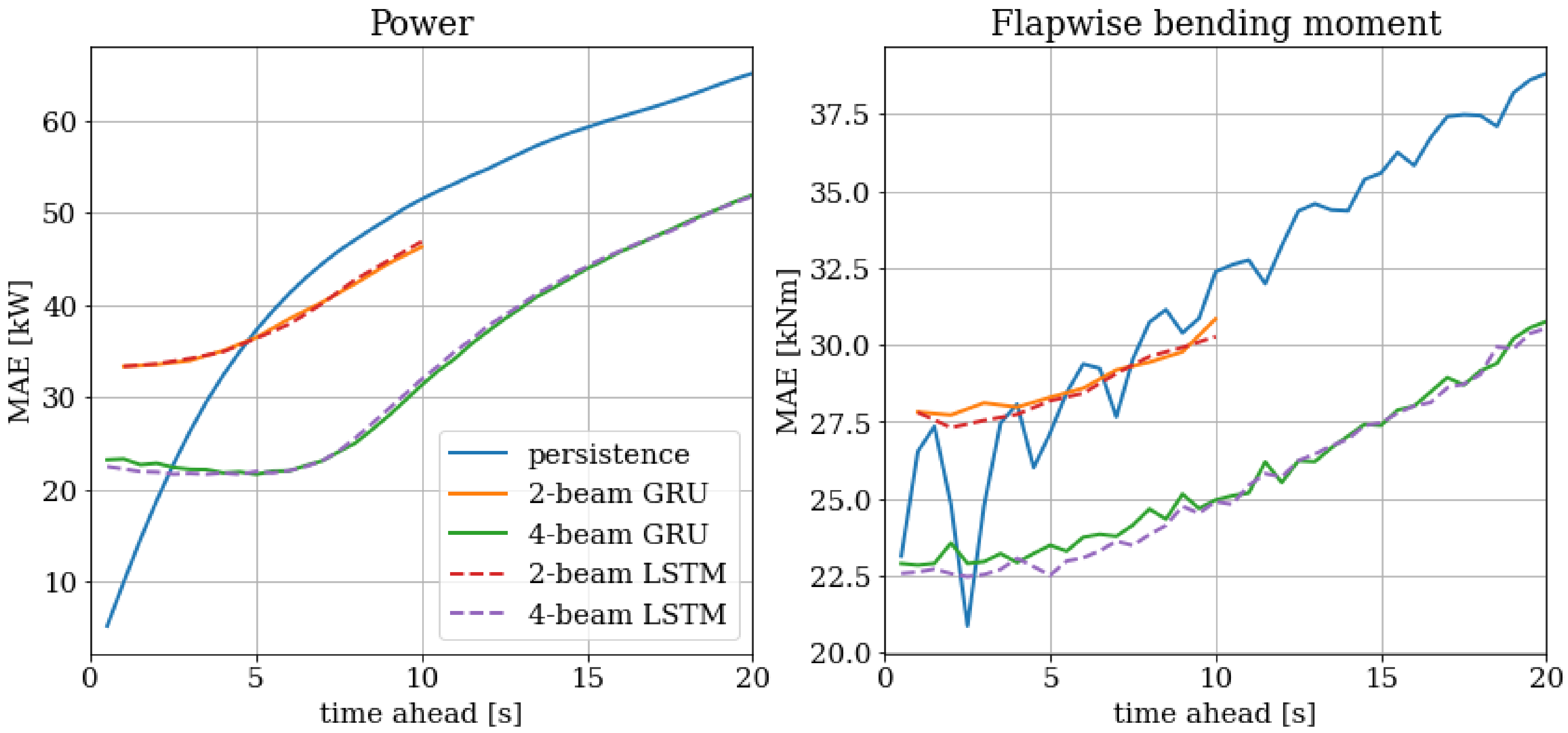


Model: "4-beamed LiDAR"

Layer (type)	Output Shape	Param #
masking (Masking)	(None, None, 9)	0
lstm (LSTM)	(None, None, 50)	12000
activation (Activation)	(None, None, 50)	0
lstm_1 (LSTM)	(None, 50)	20200
dense (Dense)	(None, 80)	4080

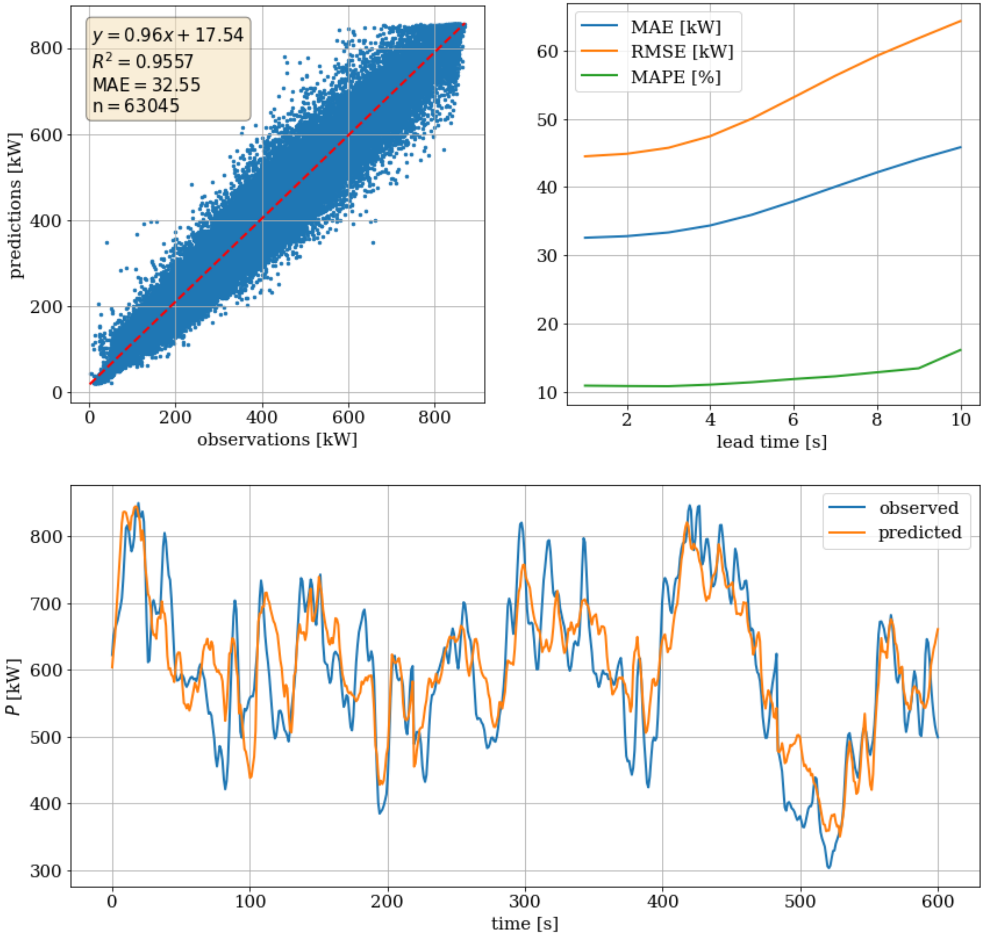
Total params: 36,280
Trainable params: 36,280
Non-trainable params: 0

Forecast horizon performance

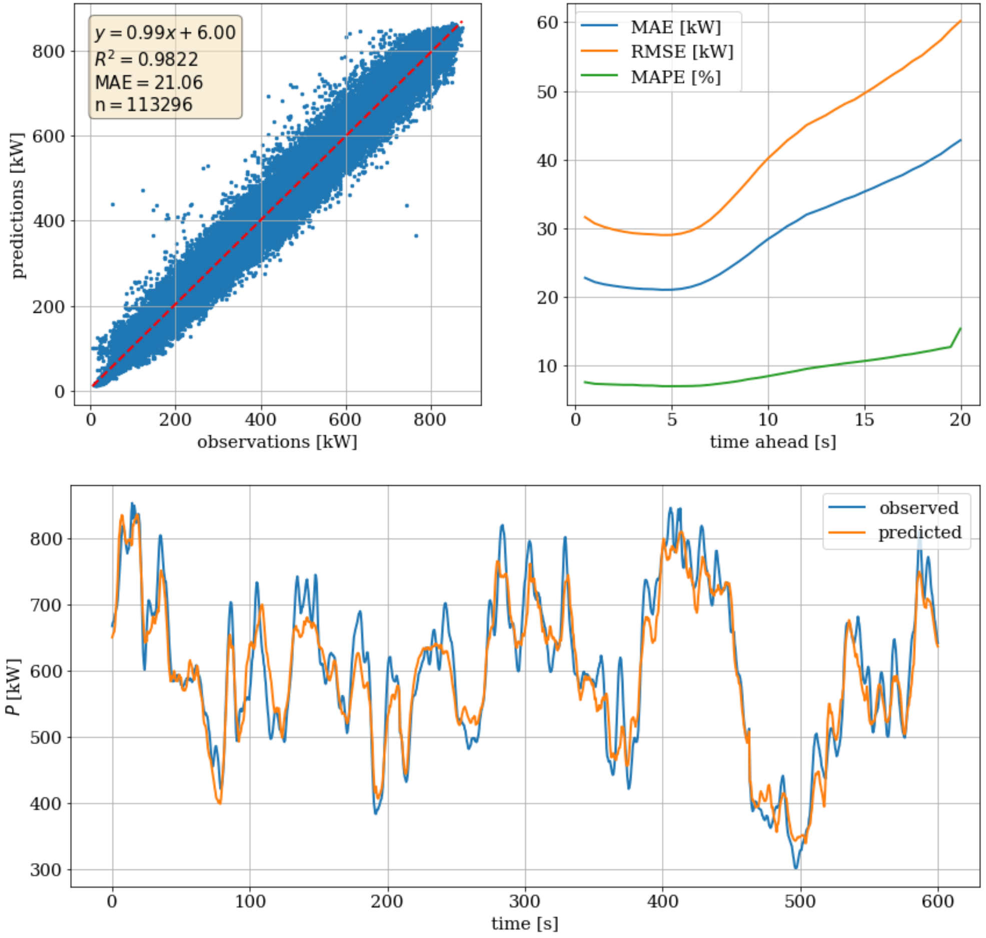


Multi-step power forecast

2-beamed LSTM model

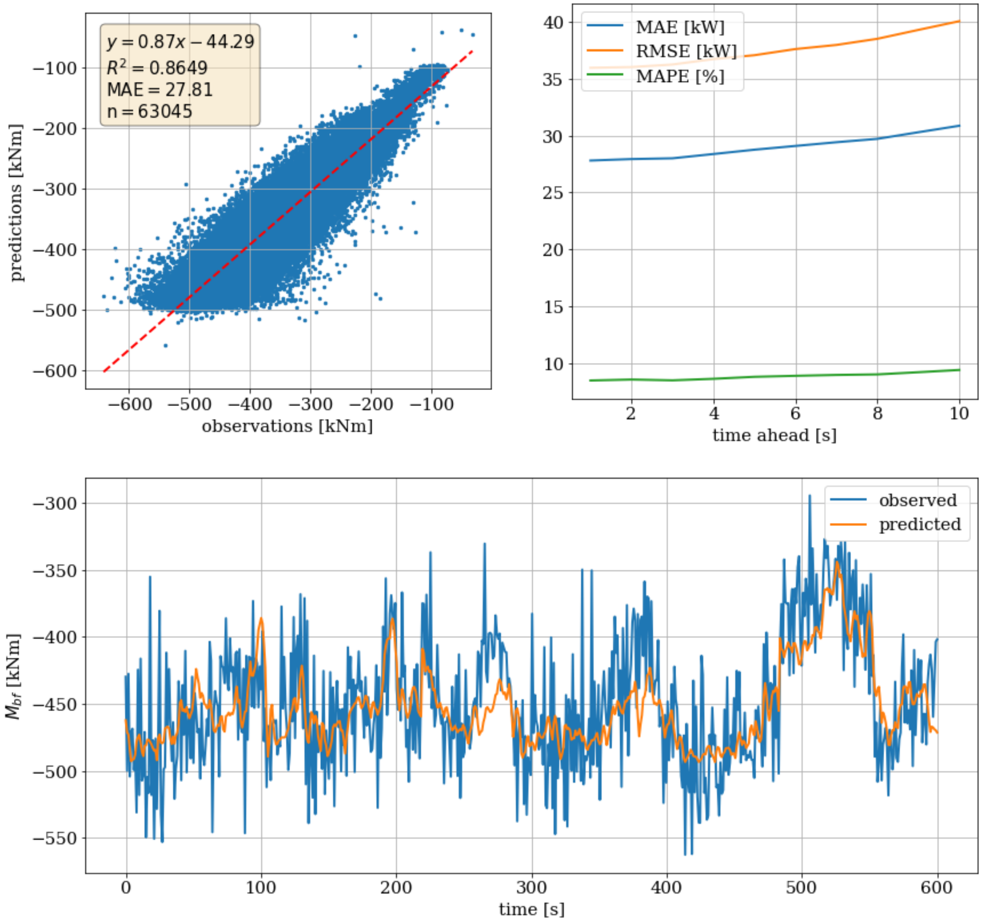


4-beamed LSTM model

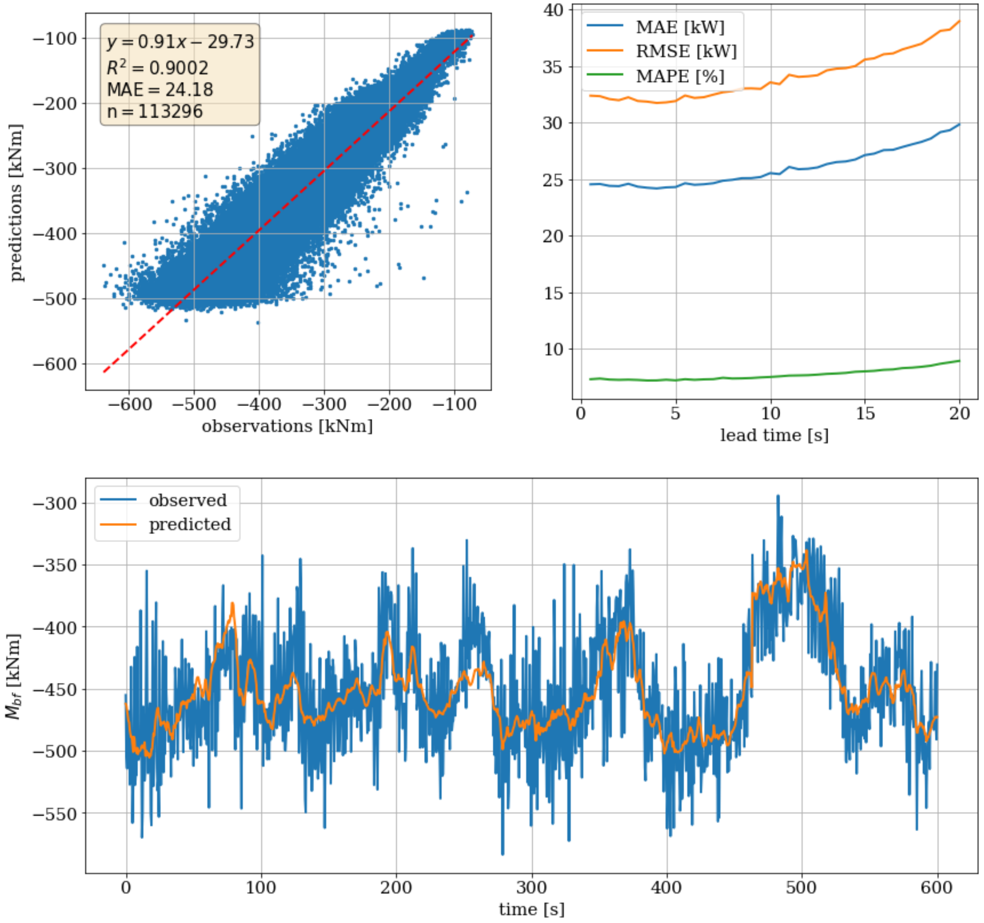


Multi-step flapwise bending moment forecast

2-beamed LSTM model

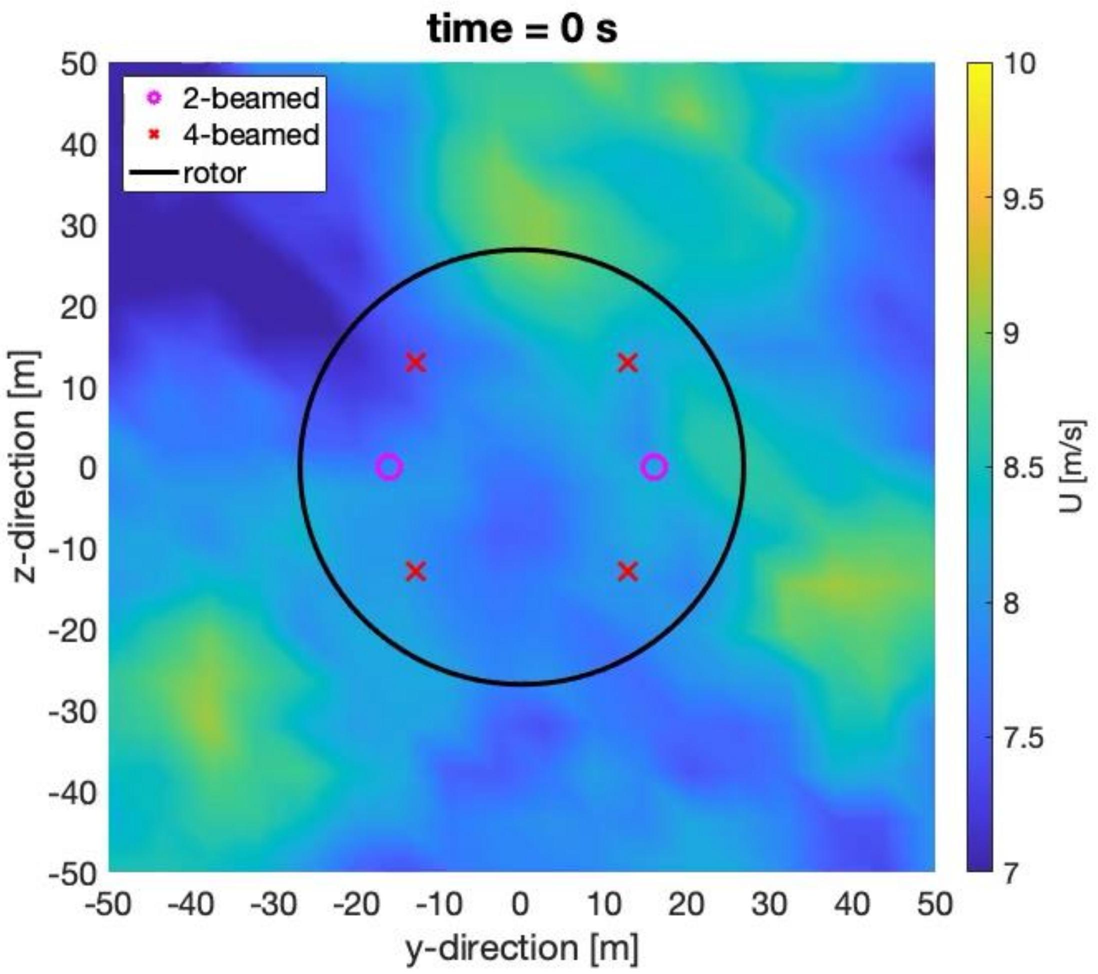


4-beamed LSTM model



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